Listen, Watch, and Learn to Feel: Retrieval-Augmented Emotion Reasoning for Compound Emotion Generation

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Abstract

The ability to comprehend human emotion using multimodal large language models (MLLMs) is essential for advancing human-AI interaction and multimodal sentiment analysis. While psychology theory-based human annotations have contributed to multimodal emotion tasks, the subjective nature of emotional perception often leads to inconsistent annotations, limiting the robustness of current models. Addressing these challenges requires more fine-grained methods and evaluation frameworks. In this paper, we propose the Retrieval-Augmented Emotion Reasoning (RAER) framework, a plug-and-play module that enhances MLLMs' ability to tackle compound and context-rich emotion tasks. To systematically evaluate model performance, we introduce the Stimulus-Armed Bandit (SAB) framework, designed to benchmark emotional reasoning capabilities. Additionally, we construct the Compound Emotion QA dataset, an AI-generated multimodal dataset aimed at strengthening emotion understanding in MLLMs. Experimental results demonstrate the effectiveness of RAER across both traditional benchmarks and SAB evaluations, highlighting its potential to enhance emotional intelligence in multimodal AI systems.

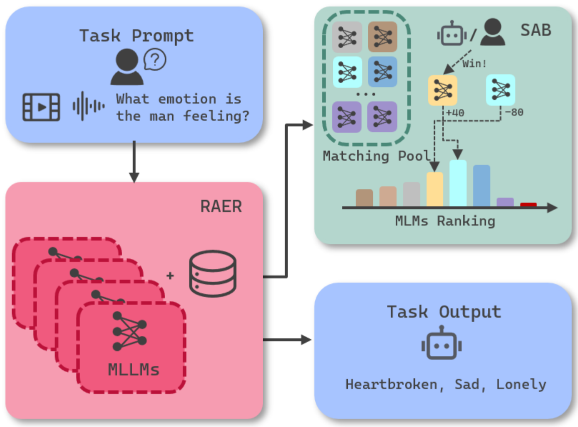


Figure 1: Overall of our proposed method and evaluation framework, where the Retrieval-Augmented Emotion Reasoning (RAER) method is introduced as a plug-and-play module to enhance the capability of MLLMs in handling compound and ambiguous emotions. The Stimulus-Armed Bandit (SAB) evaluation framework is used to assess the model's emotional capabilities, especially for tasks that are difficult to quantify.

1 Introduction

Emotion is a multifaceted phenomenon encompassing subjective experiences, physiological responses, and context-dependent behaviors, shaped by both internal states and external stimuli. Emotions play a critical role in human cognition and interaction, influencing decision-making, directing attention, and shaping social relationships. Their complexity and impact underscore the significance of emotions as a core component of human experience and behavior.

Recent advancements in neural network methods have highlighted the effectiveness of specialized models for emotion tasks. These models, which predict labels within a constrained range, have achieved impressive performance, particularly in tasks such as Dynamic Facial Emotion Recognition (DFER) (Tran et al., 2015; Wang et al., 2023; Ghaleb et al., 2019) and Multimodal Emotion Recognition (MER) (Tsai et al., 2019; Hazarika et al., 2020; Zadeh et al., 2018).

However, widely adopted annotation standards within a constrained range—such as the "Big Six" discrete label system (Ekman, 1992) and the VAD (Valence-Arousal-Dominance) dimensional label system (Russell and Mehrabian, 1977)—have proven effective in capturing emotional expression, they may not fully align with the more nuanced emotional interactions required for AI systems, particularly in the era of large models that demand more human-like interaction for emotion-related tasks. To address these limitations, approaches based on multimodal large language models (MLLMs) have emerged (Lian et al., 2024c; Cheng et al., 2024a). Tasks such as Multimodal Empathetic Response Generation (MERG) (Zhang et al., 2024a) and other emotion-related tasks (Zheng et al., 2024; Sabour et al., 2024; Plaza Del Arco et al., 2024) have shown strong performance on MLLMs, with excellent generalization capabilities. Despite these advancements, significant challenges remain in handling compound and ambiguous emotions, especially in tasks involving compound and context-rich emotional scenarios.

In this paper, as shown in Figure 2, we draw inspiration from recent advances in preference-based learning methods—such as Reinforcement Learning with Human Feedback (RLHF) (Stiennon et al., 2022), Reinforcement Learning from AI Feedback (RLAIF) (Bai et al., 2022), Direct Preference Optimization (DPO) (Rafailov et al., 2024), and Inverse Preference Optimization (IPO) (Huang et al., 2024b)—to explore a more fluid and subjective approach to evaluating emotion tasks. However, a major challenge in constructing emotion preference datasets lies in the labor-intensive process of manually drafting labels, which is not only time-consuming but also prone to inconsistencies. These inconsistencies arise from both variations in linguistic descriptions and differences in human preferences, making it difficult to disentangle the specific preference signals required for AI model training (Lian et al., 2024a; Cheng et al., 2024a).

As shown in figure.1. Instead of relying on manually curated label drafts and preference annotations, we propose a Retrieval-Augmented Emotion Reasoning (RAER) Framework, a RAG-based module that integrates chain-of-thought (CoT) reasoning. RAER can be easily applied to MLLMs, enhancing their emotional reasoning and generalization capabilities to tackle compound emotional scenarios. To evaluate MLLMs' emotional task capabilities and gather human preferences, we introduce the Stimulus-Armed Bandit (SAB) Evaluation Framework, which uses AI-generated stimuli to test a broad range of emotion tasks. This approach not only collects human preferences but also benchmarks model performance in dynamic and compound emotional contexts. By combining RAER-generated responses with SAB-collected human preferences, we construct the Compound Emotion QA Dataset, a multimodal dataset that captures nuanced emotional reasoning aligned with human preferences. This methodology bridges the gap between traditional emotion recognition and

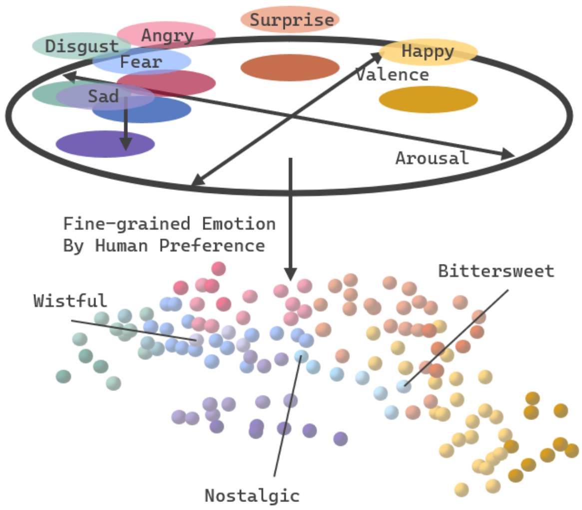


Figure 2: In linguistic contexts, the expression of human emotions is inherently open-ended, suggesting that label systems with predefined boundaries are limited in the context of large models. To enhance the emotional capabilities of these models, it is essential to adopt more human-like, nuanced approaches that allow for a broader range of emotional expression.

more compound emotional reasoning, offering a scalable and preference-aligned solution to advance emotional intelligence in MLLMs.

Main Contributions. The major contributions of this work are summarized as follows:

- **Emotion Reasoning RAG:** We propose a retrieval-augmented framework, Retrieval-Augmented Emotion Reasoning (RAER), which incorporates a chain-of-emotion reasoning approach to enhance MLLMs' capability in addressing compound emotional tasks.
- **Stimulus-Armed Bandit (SAB) Evaluation Framework:** We introduce the SAB framework to systematically evaluate MLLMs' performance in compound emotional scenarios.
- **Compound Emotion QA:** We construct a multimodal QA dataset that includes compound emotion tasks, designed to enhance the compound emotional capabilities of MLLMs.

2 Related Work

2.1 Multimodal Emotion Recognition

Multimodal Emotion Recognition (MER) aims to improve emotion detection by integrating multiple modalities. With the rise of neural network-based methods, advanced modality fusion networks have been proposed (Tsai et al., 2019; Hazarika et al., 2020; Zadeh et al., 2018), leading to significant improvements in MER. However, challenges such as high dataset labeling costs and task-specific network architectures still hinder the models' generalization in real-world scenarios.

The development of MLLMs has shown promising improvements in MER. These models, leveraging large-scale pretraining on diverse multimodal data, demonstrate enhanced generalization capabilities in emotion tasks (Lian et al., 2024c; Cheng et al., 2024a), surpassing traditional approaches in terms of flexibility and adaptability.

Moreover, the ongoing expansion of multimodal emotion recognition benchmarks and datasets has contributed significantly to this progress (Sabour et al., 2024; Lian et al., 2024c). These resources allow for more comprehensive evaluations of MLM-based models, supporting more accurate emotion detection and better alignment with real-world applications.

2.2 Multimodal Empathetic Response Generation

Multimodal empathetic response generation aims to enable machines to not only understand human emotions but also respond empathetically across various modalities. While Large Language Models (LLMs) (Zhang et al., 2024a; Yang et al., 2024), have shown potential in generating empathetic responses from textual inputs, incorporating additional modalities such as voice tone, facial expressions, and body language remains an ongoing challenge. Furthermore, the subjective nature of empathy complicates the evaluation process, making it difficult to define consistent and reliable metrics for assessing the quality of empathetic responses (Wu et al., 2024). These challenges emphasize the need for further research into better integration of multimodal data to enhance the emotional depth and reliability of empathetic response generation systems.

2.3 Retrieval-Augmented Generation

Retrieval-Augmented Generation (RAG) has proven effective in enhancing generative models' ability to generalize across tasks by incorporating external knowledge, such as in Text-to-3D (Seo et al., 2024) and Protein Molecule Generation (Huang et al., 2024d). In emotion-related tasks, RAG has been used to improve response generation by dynamically retrieving emotionally relevant data to refine models' outputs (Huang et al., 2024a; Liu et al., 2024). These approaches have been applied in areas like emotional agent (Huang et al., 2024a) and Empathetic response generation(ERC) (Huang et al., 2024c), where diverse emotional cues enhance performance.

Building on these methods, our work extends RAG to compound emotion tasks by incorporating contextual emotional knowledge from multimodal sources. This approach improves emotion recognition and generation by using dynamic, context-driven retrieval, enabling more flexible and empathetic models that can handle a wider range of emotional scenarios.

3 Retrieval-Augmented Emotion Reasoning

Emotional reasoning refers to the process of deriving conclusions based on emotional responses, even when empirical evidence may suggest otherwise. This concept has proven effective in large models for addressing compound emotion-related tasks (Lian et al., 2023), particularly those involving ambiguous or context-dependent emotional content. Building on this foundation, as shown in Figure 3, we propose Retrieval-Augmented Emotion Reasoning (RAER), a framework designed to enhance multimodal large language models (MLLMs) by integrating emotional reasoning into a structured chain-of-thought (CoT) process (Wei et al., 2023).

3.1 Building the Emotional Knowledge Base

A cornerstone of RAER is the emotional knowledge base, which serves as the foundation for retrieval during the reasoning process. Initially, the knowledge base is constructed from multimodal emotion datasets, encoding diverse inputs such as facial expression animations, emotional audio clips, and human/AI-generated emotional descriptions. Each sample is transformed into a high-dimensional vector embedding, enriched with detailed emotional annotations, enabling efficient similarity-based retrieval to support the reasoning process. As RAER engages in iterative reasoning tasks, the knowledge base evolves through the addition of high-confidence samples generated during the reasoning process. This dynamic updating mechanism not only enhances the diversity of the knowledge base but also improves its ability to provide contextually relevant emotional refer-

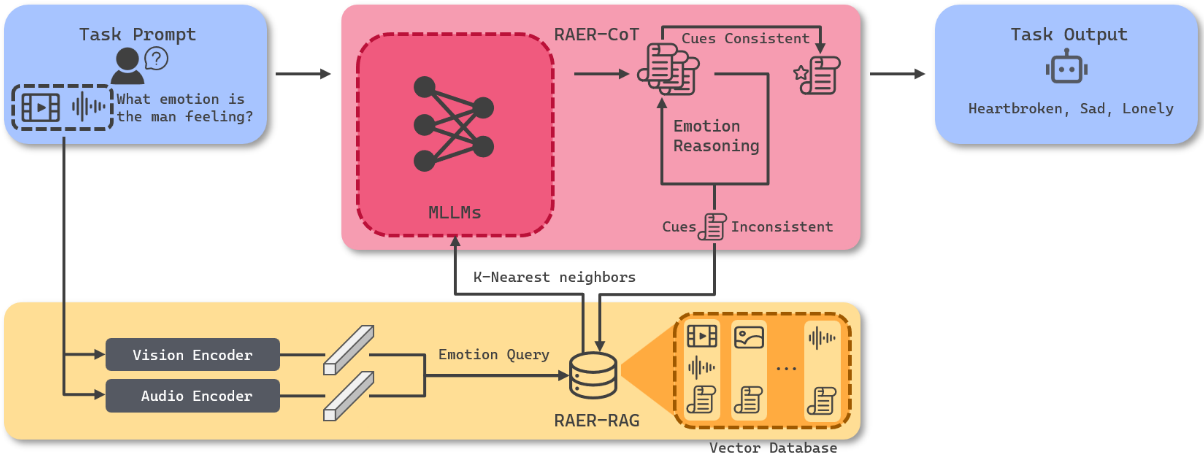


Figure 3: Overall of the RAER architecture, where a multimodal prompt is input into the model. RAER searches for the most similar content in the vector database, incorporating the Emotion Reasoning CoT process to validate the emotional consistency of the model's response. After ensuring emotional coherence, the model generates the final output.

ences. By combining curated data from traditional datasets with newly derived samples, the emotional knowledge base becomes a continuously expanding resource, progressively strengthening RAER's capacity for compound and nuanced emotional reasoning.

3.2 Guiding Emotion Reasoning with Chain-of-Thought

The RAER framework leverages a CoT reasoning mechanism to guide MLLMs through emotional reasoning tasks. This structured approach allows models to process compound emotional inputs step by step, identifying uncertainties or ambiguities within generated captions or descriptions. These challenges often arise in scenarios involving overlapping or conflicting emotional cues. To address them, RAER incorporates retrieval-based augmentation, enabling models to draw upon contextually relevant emotional information retrieved from an external knowledge base.

3.3 Enhancing Emotional Reasoning with Retrieval

Incorporating retrieval into the reasoning process allows RAG to refine the model's understanding of compound emotions. For example, when a caption reflects emotional ambiguity, the framework retrieves similar examples from the emotional knowledge base, along with their associated emotional descriptions. By grounding its reasoning in these examples, RAER enables the model to refine its understanding, disambiguate emotional cues, and generate more accurate and contextually appropriate inferences.

Algorithm 1 Retrieval-Augmented Emotion Reasoning (RAER)

Input: Task prompt I, multimodal input X (e.g., video, audio, text), knowledge base $\mathcal{K}$, MLLM f_θ
Output: Refined reasoning outputs $\{y_t\}_{t=1}^{T}$

```
Generate initial response: Y = f_θ(I, X)
Segment reasoning steps: {y_i}_{i=1}^T = Segment(f_Analyze(Y))
for t = 1 to T do
    Retrieve context: R(y_{t-1}) = Retrieve(K, Sim(y_{t-1}, K))
    if Detect(y_t, R(y_{t-1})) is ambiguous then
        Generate reasoning step: y_t = f_CoT(y_t, R(y_t))
    end if
end for
if Uncertainty(y_t) ≤ ϵ then
    Update knowledge base: K ← K ∪ {(X, {y_t}_{t=1}^T)}
end if
Return: Refined reasoning steps {y_t}_{t=1}^T
```

Through RAER, we enhance MLLMs' zero-shot capabilities for handling emotion tasks. However, to further improve model performance with human feedback, we need precise human preference signals and a method to evaluate generative models' performance on emotion tasks in open-ended language contexts. To address this, we designed the Stimulus-Armed Bandit(SAB) framework.

4 Stimulus-Armed Bandit

The Stimulus-Armed Bandit (SAB) framework is a novel evaluation method designed to assess the compound emotion capabilities of multimodal large language models (MLLMs). The name is inspired by the classic multi-armed bandit optimization problem, as emotion tasks similarly involve balancing between different emotional responses. SAB introduces a preference-based ranking system that combines multimodal stimuli with emotion tasks. Through pairwise comparisons, SAB dynamically ranks models based on their emotional reasoning, while also collecting human preferences and corresponding task labels.

The SAB framework integrates three key components to enable comprehensive and scalable evaluation:

(1) Stimulus Generation, which produces multimodal triggers to elicit emotional responses;

(2) Task Formulation, which combines stimuli with emotion-related downstream tasks to create diverse evaluation challenges; and

(3) Ranking Mechanism, which utilizes an elo-based scoring system to dynamically adjust model rankings based on their comparative performance.

4.1 Stimulus Generation and Task Formulation

Stimulus Generation. Stimuli serve as the core of the SAB framework, functioning as controlled triggers designed to evoke specific emotional and cognitive responses. To achieve this, single or multiple emotion-neutral keywords are randomly sampled, and LLMs are prompted to improvisationally generate human-centered scenario prompts. Generative models then create corresponding content based on these prompts. This approach ensures that the generated content aligns with real-world emotional scenarios rather than pre-defined emotional contexts. Leveraging AI-generated content, stimuli are dynamically delivered with diverse and non-repetitive samples across multiple modalities, including text, audio, images, and video, providing a broad spectrum of emotional triggers for evaluation.

Task Formulation. Each stimulus is paired with a corresponding downstream task commonly seen in MER or MERG, These tasks are randomly assigned to MLLMs to ensure diverse and unbiased evaluations. The randomized pairing of stimuli and tasks ensures that MLLMs are exposed to a wide range of scenarios, testing their adaptability and robustness in compound emotional contexts.

4.2 Ranking Mechanism

Initialization. All MLLMs start with identical ranking scores, ensuring a fair initial condition. The starting score is set to a predefined baseline, S_0, which is the same for all participating models.

Pairwise Matching and Preference Judgments. During each evaluation round, MLLMs are first paired based on similar ranking scores to ensure competitive and balanced matches. Let the models be denoted as $M_1, M_2, \ldots, M_N$, where each M_i has a score S_i. The models are paired such that $|S_i - S_j|$ is minimized for each match. Next, each pair of models is assigned identical stimuli and tasks drawn randomly from the task pool. For instance, if a pair M_i and M_j is matched, they both receive the same stimulus X_{stimulus} and task T_{task}.Once the stimuli and tasks are assigned, each model generates a response to the task, denoted as R_i for model M_i and R_j for model M_j. The responses R_i and R_j are then evaluated by human or AI evaluators, who compare them based on criteria such as emotional relevance, coherence, and depth of reasoning .Finally, the evaluators select the preferred response, which could be denoted as $R_{\text{preferred}}$, where:

$$R_{\text{preferred}} = \begin{cases} R_i, & \text{if model } M_i \text{ is preferred,} \\ R_j, & \text{if model } M_j \text{ is preferred.} \end{cases}$$

This process ensures a robust and contextually relevant evaluation based on human-like judgments or AI preferences.

Score Adjustment. The ranking scores are updated using an elo-based mechanism, as follows:

$$S_i^{\text{new}} = S_i^{\text{old}} + K \cdot (R - E), \tag{1}$$

where: S_i^{new} denotes the updated ranking score of model i, S_i^{old} represents the current ranking score of model i, K is the scaling factor that determines the sensitivity of score adjustments, M is a tunable parameter that controls the ranking sensitivity, R indicates the actual match outcome, where $R = 1$ if the model wins, $R = 0.5$ for a draw, and $R = 0$ if the model loses, E represents the expected match outcome, calculated as:

$$E = \frac{1}{1 + 10^{(S_j - S_i)/M}}, \tag{2}$$

where S_j is the opponent's ranking score.

Iterative Refinement. Over multiple rounds, models compete against opponents with similar scores, gradually revealing their relative strengths. This mechanism ensures fair and adaptive ranking, reflecting each model's ability to handle compound emotional tasks.

5 Experiments

In this section, we present a comprehensive evaluation of the Retrieval-Augmented Emotion Reasoning (RAER) framework. The experiments are conducted across two main categories: Traditional datasets and metrics, encompassing various tasks in Multimodal Emotion Recognition (MER) and Multimodal Empathetic Response Generation (MERG), and the novel Stimulus-Armed Bandit (SAB) evaluation framework, which systematically evaluates both visual-language and audio-language generated samples.

5.1 Implementation Details

In our experiments, the models under consideration include AffectGPT (Lian et al., 2024c), EmotionLlama (Cheng et al., 2024a), VideoLlama2 (Cheng et al., 2024b), LlavaNextVideo (Zhang et al., 2024b), Qwen2.5VL (Team, 2025), SALMONN (Sun et al., 2024), and Qwen2Audio (Chu et al., 2024). All models are evaluated using zero-shot inference, with the exception of AffectGPT and EmotionLlama, which were fine-tuned specifically for emotion tasks. All models in our experiments used a 7B parameter size. WAR (Weighted Average Recall) is employed as the evaluation metric across all datasets in MER Task evaluation, and ablation studies are conducted to examine the integration of RAER. During the course of the experiments, we find that the MLLMs of AffectGPT and EmotionLlama support a maximum context size of 2048 tokens, which lead to failures in RAER's CoT process due to the inability to retrieve the context successfully. As a result, we decide not to incorporate the RAER module into these models. We use Faiss (Douze et al., 2024) as the vector dataset for RAER, employing SBERT (Reimers and Gurevych, 2019) for encoding the textual content and CLIP (Radford et al., 2021) for encoding the visual content. The features from multiple frames are concatenated to form the query vector. For the audio content, we use AST (Gong et al., 2021)for encoding. The initial samples are derived from the 332 labeled entries in the EMER-finev2 (Lian et al., 2024a) dataset. For the SAB evaluation, we use GPT-4 to generate task prompts, OpenAI's Sora for visual-language evaluation, and Meta's AudioGen (Kreuk et al., 2022) for audio-language evaluation. Since no generative model currently exists that can simultaneously produce visual, audio, and language modalities, we are unable to perform SAB evaluation on VAT samples. The experiments are conducted using four NVIDIA H800 80GB GPUs and the hyper-parameter of RAER and SAB can be found in Appendix A.

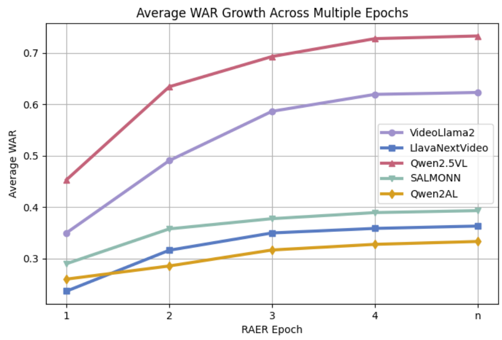


Figure 4: In the RAER framework, correctly predicted samples from the dataset are added to the vector database and referenced in subsequent predictions. After multiple rounds of this process, the model demonstrates significant performance improvements, as shown by the average WAR growth across epochs.

5.2 Traditional Benchmarks Evaluation

MER Tasks Evaluation. As shown in Table 7. We conduct a comprehensive evaluation of REAR's impact on the emotional capabilities of various multimodal large language models (MLLMs) through ablation studies. Further details can be found in Appendix B. Models are evaluated on three widely recognized multimodal emotion recognition (MER) datasets: MER2024 (Lian et al., 2024b), DFEW (Jiang et al., 2020), and IEMOCAP (Busso et al., 2008). In our experiments, Qwen2.5VL demonstrates remarkable performance. Despite the absence of audio modality information, Qwen2.5VL-RAER still achieves a WAR score of over 0.7 across three datasets, outperforming both AffectGPT and EmotionLlama, which had been fine-tuned on the MER task in a zero-shot setting. Additionally, we observed that visual information contributed more significantly to performance improvements compared to audio information. The experimental results consistently demonstrate that REAR significantly enhances the emotion recognition perfor-

				MER2024		DFEW		IEMOCAP	
MLLMs	V	A	T	w/o RAER	RAER	w/o RAER	RAER	w/o RAER	RAER
AffectGPT	✓	✓	✓	**0.64**	-	0.52	-	**0.71**	-
EmotionLlama	✓	✓	✓	0.23	-	**0.59**	-	0.32	-
VideoLlama2	✓	✓	✓	0.35	0.62	0.32	0.66	0.41	0.71
LlavaNextVideo	✓	✗	✓	0.23	0.37	0.22	0.32	0.28	0.40
Qwen2.5VL	✓	✗	✓	0.45	**0.73**	0.43	**0.69**	0.53	**0.78**
SALMONN	✓	✓	✗	0.31	0.42	0.24	0.37	0.34	0.39
Qwen2Audio	✓	✓	✗	0.27	0.35	0.22	0.28	0.31	0.37

Table 1: The results of MER tasks are presented, where WAR is used as the evaluation metric. All results are obtained using zero-shot inference.

	BLEU		Dist-1/2		ROU_L.		MET.		BERTS.	
MLLMs	w/o RAER	RAER	w/o RAER	RAER	w/o RAER	RAER	w/o RAER	RAER	w/o RAER	RAER
AffectGPT	0.13	-	0.56/0.82	-	0.17	-	0.31	-	**0.87**	-
EmotionLlama	0.10	-	0.54/0.79	-	0.15	-	0.28	-	0.85	-
VideoLlama2	**0.22**	0.24	0.71/0.92	0.69/0.92	**0.23**	0.24	0.31	**0.40**	0.83	0.87
LlavaNextVideo	0.17	0.22	0.69/0.87	0.71/0.86	0.19	0.2	0.28	0.25	0.79	0.83
Qwen2.5VL	0.21	**0.25**	**0.74/0.95**	**0.77/0.95**	**0.23**	**0.25**	**0.33**	0.36	0.86	**0.91**
SALMONN	0.18	0.17	0.72/0.88	0.72/0.89	0.17	0.21	0.23	0.25	0.81	0.85
Qwen2Audio	0.15	0.22	0.68/0.85	0.69/0.87	0.18	0.22	0.25	0.27	0.83	0.86

Table 2: The results of the automatic evaluation of MERG tasks are presented, with all outcomes obtained through zero-shot inference.

mance of these MLLMs, highlighting its robust ability to improve emotional comprehension across diverse multimodal contexts.

MERG Tasks Evaluation. As shown in Figure Table 2, We first conducted automated evaluations using several standard metrics, including BLEU (Papineni et al., 2002), Dist-1/2 (Li et al., 2016), ROUGE-L (Lin, 2004), METEOR (Banerjee and Lavie, 2005), and BERTScore (Zhang et al., 2020). Following the previous approaches (Wu et al., 2025; Zhang et al., 2024a; Fei et al., 2024), we also designed human evaluation protocols to assess various aspects such as response empathy, linguistic fluency, and consistency in Table 3. In our experiments, REAR significantly improved the model's consistency while preserving its generalization ability, with no noticeable decline in empathy or fluency.

	Emp./Con./Flu. (Human Evaluation)	
MLLMs	w/o RAER	RAER
AffectGPT	2.32/3.29/2.45	-
EmotionLlama	2.24/3.37/2.37	-
VideoLlama2	3.42/3.22/3.53	3.44/3.34/3.54
LlavaNextVideo	2.72/2.92/3.12	2.78/3.07/3.13
Qwen2.5VL	**3.76/3.46/3.78**	**3.74/3.78/3.76**
SALMONN	3.17/3.25/3.38	3.16/3.35/3.23
Qwen2Audio	3.24/3.32/3.42	3.26/3.42/3.35

Table 3: The results of the human evaluation of MERG tasks are presented, with all outcomes obtained through zero-shot inference.

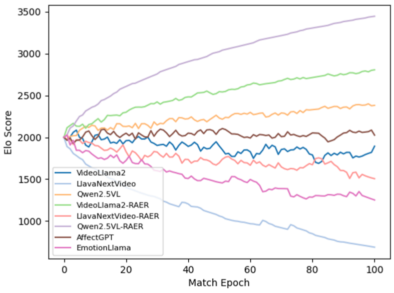
5.3 Stimulus-Armed Bandit Evaluation

In the Stimulus-Armed Bandit (SAB) evaluation, we randomly generate one or a few emotion-neutral keywords and use generative models to produce corresponding stimuli. For this process, we employ GPT-4o to generate prompts, Sora for visual stimuli, and AudioGen for audio stimuli, further details can be found in Appendix C. Each evaluation match randomly selects a task from a predefined task pool, which is then combined with the generated stimuli to create a task prompt. The paired models are then tasked with providing the most suitable responses to the prompt. These responses are evaluated based on human or GPT-4o preferences, and the SAB framework uses an Elo-based scoring mechanism. The winning model gains points, while the losing model's score is adjusted accordingly.

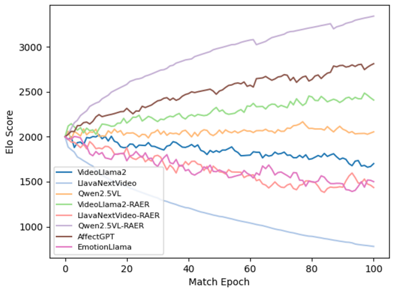
In our experiments, as shown in Figure 5, most task pools converged after approximately 100 rounds, and the resulting model rankings align with those obtained in traditional benchmark evaluations. This demonstrates that the SAB framework effectively leverages human-like preferences to comprehensively evaluate the emotional reasoning and generation capabilities of multimodal large language models.

5.4 Compound Emotion QA Construction

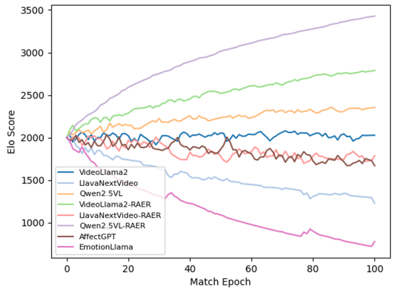
We compiled the results from the SAB evaluation into two sub-datasets, as shown in Table 4. Each sample is annotated with preferred and non-preferred responses, as illustrated in Figure 6.



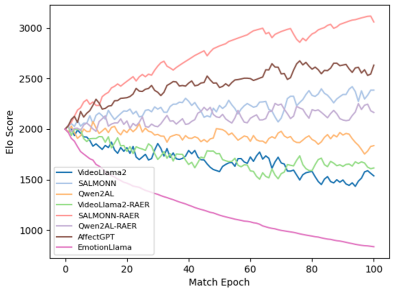
(a) Mixed Task on Visual-Language



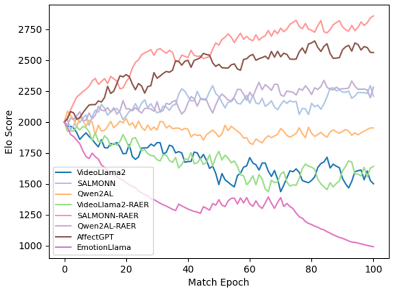
(b) MER Task on Visual-Language



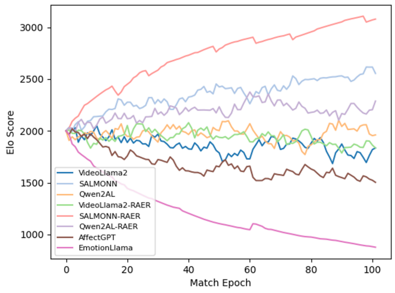
(c) MERG Task on Visual-Language



(d) Mixed Task on Audio-Language



(e) MER Task on Audio-Language



(f) MERG Task on Audio-Language

Figure 5: Part of the SAB evaluation results, where we used three task pools: Mixed, MER, and MERG. Figures (a), (b), and (c) evaluate visual-language capabilities, while figures (d), (e), and (f) assess audio-language capabilities. Most models' Elo scores remain relatively stable between upper and lower bounds, indicating that the models' abilities are accurately assessed through multiple rounds of testing.

Task Prompt:
The man is reading under the starry sky. Analyze the person's emotions.

Preferred:
The man in the image appears focused and engaged in reading, with his gaze directed upwards, indicating concentration. The setting in the background, with the starry sky, might evoke a sense of curiosity or contemplation, suggesting a calm and reflective emotional state.

Non-Preferred:
Although the man seems engaged in his reading, his slightly furrowed brow and neutral expression might indicate a sense of confusion or frustration, particularly if the reading material is challenging or not well-understood. The ambient lighting and background could imply a more tense or serious emotional state.

Figure 6: An example of SAB collected human preferences and corresponding task labels.

Data type	Human Preference	GPT-4 Preference
VL	240	760
AL	1000	0

Table 4: Number of samples for Visual-Language (VL) and Audio-Language (AL) datasets, with preferences by human evaluators and GPT-4.

Based on this, we fine-tuned VideoLLama2 using Direct Preference Optimization (DPO) and conducted experiments on the MER task. The ablation experiment results are presented in Table 5. The findings suggest that our Compound Emotion QA dataset leads to an improvement in model performance.

	MER2024	DFEW	IEMOCAP
VideoLlama2	0.35	0.32	0.41
w/ DPO	0.48	0.41	0.53
w/ RAER	0.62	**0.66**	0.71
w/ DPO&RAER	**0.67**	0.65	**0.79**

Table 5: The ablation experiment on DPO and RAER, with all metrics evaluated using WAR.

6 Conclusion

In this paper, we introduced the Retrieval-Augmented Emotion Reasoning (RAER) framework, which enhances multimodal large language models (MLLMs) by combining emotional reasoning with retrieval-augmented processes. Our experiments on standard benchmarks and the Stimulus-Armed Bandit (SAB) evaluation demonstrate RAER's effectiveness in handling compound emotional tasks. We also contributed the Compound Emotion QA dataset, an AI-generated dataset designed to further improve emotional reasoning. The results highlight RAER's potential in advancing multimodal sentiment analysis and enhancing human-AI interaction.

Limitations

Although our study presents promising advancements, it is not without its limitations. Firstly, while we aim for full automation, current state-of-the-art multimodal models still fall short in aligning with human preferences in audio. Although preference-based methods reduce the cost of manual selection, SAB cannot yet be fully automated. Secondly, RAER requires longer inference times compared to regular reasoning methods, leading to significantly lower computational efficiency. We are exploring more advanced CoT methods to potentially replace the current approach. Additionally, we utilize generative models to generate samples; however, there is currently no VAT-enabled (Visual,Audio,Text) generative model that covers all three modalities. As such, the SAB evaluation framework cannot fully replace traditional evaluation methods at this stage. Lastly, while RAER leverages human preferences at the annotation level, we are considering extending this by incorporating human feedback learning to further capitalize on the preference data generated during the RAER process.

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A Hyperparameters

We set key hyperparameters to optimize the RAER and SAB frameworks. For RAER, K is set to 5. In SAB, K=64, M=600 control sample size, and sequence length, while new_output_token=500 limits output length. Temperature=0.7 and top_p=0.9 adjust generation randomness, balancing diversity and quality. These settings were chosen based on prior experiments for optimal performance.

Hyperparameter	Value
RAER	K=5
SAB	K=64, M=600, new_output_token=500, temperature=0.7, top_p=0.9

Table 6: Hyperparameters for RAER and SAB

					MER2024 w/o RAER				
	Acc↑	Acc↑	Acc↑	Acc↑	Acc↑	Acc↑	Acc↑	UAR↑	WAR↑
MLLMs	Worried	Happy	Neutral	Angry	Surprise	Sad			
AffectGPT	0.87	0.83	0.00	0.67	0.12	0.78		0.57	0.64
EmotionLlama	0.55	0.12	0.00	0.25	0.06	0.19		0.21	0.23
VideoLlama2	0.76	0.38	0.26	0.21	0.00	0.40		0.34	0.35
LlavaNextVideo	0.62	0.32	0.21	0.12	0.00	0.08		0.22	0.23
Qwen2.5VL	0.20	0.58	1.00	0.06	0.00	0.38		0.37	0.45
SALMONN	0.52	0.48	0.32	0.15	0.00	0.12		0.28	0.31
Qwen2Audio	0.21	0.39	0.62	0.12	0.00	0.11		0.25	0.27
					MER2024 RAER				
MLLMs	Worried	Happy	Neutral	Angry	Surprise	Sad			
VideoLlama2	0.83	0.68	0.83	0.42	0.00	0.54		0.56	0.62
LlavaNextVideo	0.74	0.33	0.42	0.24	0.00	0.08		0.33	0.37
Qwen2.5VL	0.78	0.84	0.92	0.66	0.00	0.46		0.65	0.73
SALMONN	0.56	0.48	0.32	0.27	0.00	0.35		0.39	0.42
Qwen2Audio	0.38	0.45	0.72	0.16	0.00	0.09		0.33	0.35
					DFEW w/o RAER				
MLLMs	Happy	Fear	Neutral	Angry	Surprise	Sad	Disgust		
AffectGPT	0.83	0.64	0.00	0.52	0.21	0.69	0.00	0.41	0.52
EmotionLlama	0.15	0.12	0.00	0.25	0.09	0.19	0.00	0.14	0.59
VideoLlama2	0.34	0.28	0.26	0.21	0.22	0.25	0.00	0.25	0.32
LlavaNextVideo	0.18	0.12	0.11	0.12	0.07	0.08	0.00	0.14	0.22
Qwen2.5VL	0.59	0.38	0.85	0.24	0.32	0.31	0.00	0.38	0.43
SALMONN	0.25	0.12	0.21	0.23	0.11	0.07	0.00	0.17	0.24
Qwen2Audio	0.32	0.16	0.24	0.07	0.02	0.11	0.00	0.14	0.22
					DFEW RAER				
MLLMs	Happy	Fear	Neutral	Angry	Surprise	Sad	Disgust		
VideoLlama2	0.63	0.44	0.57	0.52	0.47	0.39	0.00	0.45	0.66
LlavaNextVideo	0.32	0.19	0.25	0.17	0.25	0.22	0.00	0.24	0.32
Qwen2.5VL	0.64	0.49	0.92	0.36	0.37	0.48	0.00	0.49	0.69
SALMONN	0.31	0.17	0.32	0.29	0.21	0.17	0.00	0.26	0.37
Qwen2Audio	0.33	0.19	0.23	0.14	0.03	0.19	0.00	0.22	0.28
					IEMOCAP w/o RAER				
MLLMs	Happy	Sad	Neutral	Angry					
AffectGPT	0.90	0.84	0.00	0.77				0.62	0.71
EmotionLlama	0.25	0.43	0.00	0.25				0.25	0.32
VideoLlama2	0.42	0.38	0.43	0.22				0.38	0.41
LlavaNextVideo	0.33	0.22	0.30	0.14				0.27	0.28
Qwen2.5VL	0.51	0.42	0.86	0.31				0.51	0.53
SALMONN	0.35	0.31	0.22	0.26				0.31	0.34
Qwen2Audio	0.45	0.22	0.34	0.15				0.30	0.31
					IEMOCAP RAER				
MLLMs	Happy	Sad	Neutral	Angry					
VideoLlama2	0.77	0.68	0.69	0.57				0.70	0.71
LlavaNextVideo	0.51	0.32	0.44	0.28				0.37	0.40
Qwen2.5VL	0.85	0.72	0.85	0.61				0.77	0.78
SALMONN	0.44	0.36	0.23	0.35				0.39	0.39
Qwen2Audio	0.57	0.25	0.39	0.17				0.36	0.37

Table 7: Detailed results of MER tasks are presented. All results are obtained using zero-shot inference.

Task	Description
Multi-choice	Select the most appropriate emotions from a predefined list based on multimodal inputs.
Ranking	Rank emotions from a predefined list based on multimodal inputs.
Recognition Analysis	Analyze and identify emotions in the multimodal input.
Transition Detection	Detect emotional shifts over time and identify when and how emotions change in a sequence.

Table 8: Multimodal Emotion Recognition (MER) Task Set Description

Task	Description
Emotion-based Response Generation	How would you feel if you were in the person's shoes in this video?
Emotion-based Response Generation	How does the person's experience in the video make you feel?
Emotion-based Response Generation	How does the video make you reflect on your own emotions or experiences?
Emotion-based Response Generation	What would you be feeling right now?

Table 9: Multimodal Empathetic Response Generation (MERG) Task Set Description

B MER Experiments Details

Table 7 presents specific metrics for each dataset in the MER task.

C SAB Task Formulation

As shown in Figure 7, we first use GPT-4 to generate one or more emotionally neutral words. These neutral words are then used to generate corresponding modality-specific stimuli for the generative model. Afterward, the corresponding task and stimuli are matched, forming an SAB sample, the tasks are shown in Table 8 and Table 9.

As shown in Table 10, we tested GPT-4o's alignment with human preferences in the SAB visual-language evaluation. The experiment shows that GPT-4o is largely aligned with human preferences and can automatically evaluate and generate positive and negative samples.

Alignment	Number of Samples	Rate
Consistent	228	76%
Inconsistent	72	24%

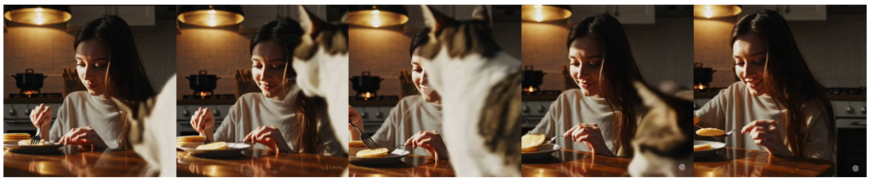
Table 10: GPT-4o's alignment with human preferences in SAB visual-language evaluation.

Emotion-Neutral Words Generation Prompt:
Randomly Generate K(Human Set) Emotion-Neutral Words

CAT PANCAKE FIRE

Stimuli Generate Prompt:
Create a video centered around a single character based on my three prompt words, showing the character's face

Prompt Words: CAT PANCAKE FIRE



Formulate Task Prompt:

Rank emotions from {predefined list(e.g. Happy, Sad, Disgust, Angry, Surprise, Fear)} based on multimodal inputs.

SAB

Preferred! Happy, Surprise, Fear, Sad, Angry, Disgust

Surprise, Happy, Disgust, Fear, Angry, Sad

Figure 7: An example of SAB task formulation