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Cross-Lingual Zero-Shot Emotion Recognition in Conversational AI Using Self-Supervised Contrastive Learning

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Abstract:

Emotion recognition in conversational artificial intelligence systems has rapidly advanced with the adoption of transformer-based architectures, yet performance across diverse languages remains limited by the scarcity of annotated multilingual datasets. This study proposes a cross-lingual zero-shot emotion recognition framework based on self-supervised contrastive learning to bridge linguistic gaps and enhance emotion understanding in

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unseen languages. The model leverages multilingual transformer encoders trained with a dual-view contrastive objective that aligns semantically similar utterances across languages while maintaining discriminative emotion boundaries. Large-scale unlabeled conversational corpora are utilized for pretraining, followed by fine-tuning on emotion-labeled English data to evaluate transfer efficiency to non-English languages such as Hindi, Spanish, and Arabic. Experimental results demonstrate significant improvements in F1-scores and cross-lingual generalization compared to conventional supervised baselines. The findings indicate that self-supervised contrastive learning can effectively encode affective information invariant to linguistic structure, enabling scalable and language-agnostic emotion understanding for next-generation conversational AI systems.

Keyword: Cross-lingual emotion recognition, Zero-shot learning, Self-supervised learning, Contrastive representation learning, Multilingual transformers, Conversational AI.

I. INTRODUCTION

Emotion recognition in conversational artificial intelligence (AI) has become a crucial component for developing systems capable of natural, empathetic, and context-aware interactions. With the increasing reliance on chatbots, virtual assistants, and social robots, identifying and responding to human emotions has transformed from an experimental concept to a necessary functionality. However, most existing emotion recognition models are heavily language-dependent and require large annotated corpora to achieve robust performance. Such data is abundantly available in English but remains scarce or inconsistent across low-resource languages. This disparity has created a major bottleneck for deploying emotionally intelligent AI in multilingual contexts. The challenge lies not only in linguistic diversity but also in the cultural nuances that shape emotional expression and context interpretation. Conventional supervised learning models such as BERT, RoBERTa, and their multilingual variants like mBERT or XLM-R, although powerful in language modelling, tend to exhibit degradation in emotion classification when exposed to zero-shot or cross-lingual scenarios. The absence of aligned emotional labels across languages hinders generalization, forcing models to rely on word-level associations rather than emotion-level abstractions. Consequently, conversational agents trained in one language often fail to interpret affective intent when the input language shifts, leading to emotionally tone-deaf interactions. Addressing this limitation requires an approach that can capture universal emotional cues, irrespective of linguistic boundaries, and encode them in a language-agnostic representation space.

To address this gap, the present study introduces a self-supervised contrastive learning framework for cross-lingual zero-shot emotion recognition in conversational AI. The proposed approach leverages unlabelled multilingual conversational datasets to pretrain a transformer encoder that aligns semantically similar utterances across different languages within a shared embedding space. The central idea is that emotions such as happiness, anger, or sadness manifest through diverse linguistic expressions but share similar semantic and prosodic patterns at a latent representational level. Through contrastive learning, the model is encouraged to minimize the distance between emotionally equivalent utterances from different languages while maximizing the distance between semantically dissimilar pairs. This process yields embeddings that capture emotional intent independent of the input language. Subsequently, the pretrained encoder is fine-tuned on labelled English emotion datasets, allowing for zero-shot transfer to other languages without direct supervision. Experimental evaluations on multilingual benchmarks demonstrate that the proposed model achieves superior cross-lingual generalization compared to supervised and translation-based baselines. The framework effectively bridges linguistic boundaries and enhances emotional understanding, contributing toward the development of inclusive and culturally adaptable conversational systems. By integrating contrastive learning principles with multilingual representation learning, this research underscores a significant step toward achieving emotionally intelligent AI capable of understanding users from diverse linguistic and cultural backgrounds.

II. RELEATED WORKS

Research on emotion recognition in conversational artificial intelligence has evolved significantly over the past decade, transitioning from traditional feature-engineered models to sophisticated deep learning architectures

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capable of capturing semantic and affective nuances in text [1]. Early approaches to emotion recognition primarily relied on lexicon-based sentiment analysis and statistical feature extraction methods such as bag-of-words, TF-IDF weighting, and part-of-speech tagging [2]. While effective for basic polarity detection, these methods lacked contextual sensitivity and were unable to model the subtleties of emotion conveyed in natural dialogues. The introduction of deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), brought substantial improvements by allowing hierarchical feature learning from raw text [3]. Recurrent architectures like LSTM and GRU could track emotional dynamics across conversational turns, improving classification accuracy [4]. However, these models were inherently language-specific and required extensive labelled data, limiting their scalability to multilingual environments [5]. The emergence of transformer-based models, such as BERT and GPT, marked a paradigm shift in emotion recognition research [6]. Pretrained on massive text corpora, these models captured both syntactic and semantic information, leading to state-of-the-art results in emotion and sentiment detection tasks [7]. Multilingual extensions such as mBERT and XLM-R expanded this potential to multiple languages, yet studies observed that their zero-shot transfer capabilities remained weak when applied to emotion recognition [8]. This limitation stemmed from the fact that multilingual transformers are optimized for general cross-lingual language understanding but not for affective semantics. Emotional content often depends on cultural and contextual cues that are not preserved through standard translation or shared embeddings [9]. Consequently, while cross-lingual sentiment analysis has seen progress, emotion recognition across languages still faces considerable challenges, especially in conversational data where tone, pragmatics, and context shift frequently [10].

Recent research trends have thus focused on integrating self-supervised and contrastive learning methods to overcome the dependency on labelled data and enhance cross-lingual transfer [11]. Self-supervised learning frameworks, such as SimCLR, MoCo, and BYOL, introduced contrastive loss mechanisms to learn representations that capture semantic consistency without requiring manual annotation [12]. When applied to natural language processing, contrastive learning has been shown to improve semantic alignment across languages by creating shared embedding spaces that link semantically equivalent sentences [13]. Studies like InfoXLM and LaBSE demonstrated that cross-lingual sentence alignment can be achieved through contrastive objectives, enabling models to learn language-agnostic features [14]. Building on these foundations, researchers in emotion recognition have begun exploring self-supervised architectures for affective representation learning. For example, models like MELD-BERT and DialogueGCN combine contextualized embeddings with emotion propagation networks to account for inter-speaker emotional dependencies [15]. However, these frameworks remain primarily monolingual. More advanced models like mT5 and XLM-R++ have attempted zero-shot emotion recognition by fine-tuning multilingual transformers on English datasets and testing on non-English corpora, but the results show consistent drops in performance due to limited emotional transferability [3]. A few recent works, such as CrossEmo and EmoAlign, have specifically adopted contrastive objectives to align emotion representations across languages using parallel and pseudo-parallel corpora [5]. These studies reported encouraging improvements in cross-lingual emotion recognition, demonstrating that emotional equivalence can be learned even without direct supervision [6]. Nevertheless, most of these models depend on translation-based data alignment, which introduces semantic distortion and cultural bias [7]. The current research differs by adopting a purely self-supervised approach that eliminates translation dependency, instead aligning utterances based on contextual similarity derived from multilingual conversational embeddings [8]. This direction merges the strengths of self-supervised representation learning with the requirements of affective computing, promoting a scalable, data-efficient framework for cross-lingual emotion understanding [9]. The combination of contrastive alignment, multilingual pretraining, and zero-shot evaluation offers a promising pathway to achieve emotionally aware AI systems capable of understanding diverse linguistic and cultural expressions without explicit human annotation [10]. An additional research direction in related works focuses on the integration of multimodal data sources such as audio, facial expressions, and physiological cues to complement textual emotion recognition across languages. Several studies have shown that combining linguistic and acoustic modalities can significantly enhance emotion classification accuracy, particularly in spontaneous conversations where text alone may lack sufficient affective cues. Furthermore, emerging cross-lingual studies are exploring graph neural networks and meta-learning to model

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emotion dependencies between speakers in multilingual dialogues. These developments indicate a gradual shift toward unified, multimodal, and linguistically adaptive emotion recognition systems that move beyond text-based emotion inference to achieve a holistic understanding of human affect in real-world interactions.

III. METHODOLOGY

3.1 Research Design

This study adopts a self-supervised and data-efficient research design aimed at enabling cross-lingual zero-shot emotion recognition without relying on annotated multilingual datasets [16]. The proposed model utilizes a dual-stage framework comprising a self-supervised contrastive pretraining phase followed by supervised fine-tuning on an English emotion corpus. The pretraining objective focuses on maximizing semantic and emotional alignment across multilingual utterances, whereas the fine-tuning phase refines the model for emotion classification. The model architecture is built upon a multilingual transformer encoder that processes contextualized embeddings of text utterances. These embeddings are passed through a projection head that optimizes a contrastive loss, encouraging emotionally similar samples to have closer representations in the shared embedding space. The model is evaluated on both seen (English) and unseen (non-English) languages to determine zero-shot generalization capability. This approach provides a scalable and language-agnostic framework for emotion recognition across diverse linguistic environments [17].

3.2 Datasets and Preprocessing

The research incorporates both labelled and unlabelled datasets from multilingual sources to train and evaluate the model. The unlabelled corpus consists of open-domain conversational datasets such as OpenSubtitles, Multilingual Reddit, and CC100 for self-supervised pretraining, while labelled datasets like GoEmotions, MELD, and EmoLL are used for fine-tuning and evaluation [18]. All textual data undergo normalization, tokenization using SentencePiece, and removal of non-textual artifacts such as emojis and punctuation inconsistencies. To ensure cross-lingual consistency, all datasets are mapped to ISO language codes and aligned at the sentence level using LASER embeddings.

Table 1: Dataset Overview for Pretraining and Fine-tuning

Dataset Name	Language(s)	Data Type	Samples Used	Purpose
CC100	Multilingual (100+)	Unlabelled Conversations	2M	Self-supervised Pretraining
OpenSubtitles	50+ Languages	Movie Dialogues	1.2M	Multilingual Semantic Alignment
GoEmotions	English	Reddit-based Text	58K	Supervised Fine-tuning
MELD	English	Dialogue (Multimodal)	13K	Evaluation
EmoLL	Hindi, Spanish, Arabic	Text Dialogue Data	12K	Zero-Shot Evaluation

Data augmentation techniques, such as back-translation and synonym substitution, were applied during pretraining to enrich the diversity of multilingual samples and avoid overfitting. Special tokens were inserted to represent speaker roles and emotional states for improved contextual tracking.

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3.3 Model Architecture

The proposed architecture integrates a multilingual transformer backbone (XLM-R base) with an emotion projection head for contrastive learning [19]. The transformer encoder extracts contextualized embeddings from input utterances, while the projection head maps these embeddings into a lower-dimensional latent space optimized through a contrastive loss function. The architecture is designed to promote inter-lingual alignment by minimizing distance between semantically equivalent utterances and maximizing separation between dissimilar pairs.

Table 2: Model Configuration and Parameters

Component	Description	Key Parameters
Transformer Encoder	XLM-R Base (12 layers)	Hidden Size: 768, Attention Heads: 12
Projection Head	Two-layer MLP	Layer Sizes: [768, 256]
Contrastive Loss	InfoNCE Objective	Temperature: 0.07
Optimizer	AdamW	Learning Rate: 2e-5
Training Batch Size	128	Epochs: 20

The loss function for contrastive learning is defined as:

$$L = -\log \left[\exp(\text{sim}(z_i, z_j)/\tau) / \Sigma_k \exp(\text{sim}(z_i, z_k)/\tau) \right]$$

where $sim(z_i, z_j)$ represents the cosine similarity between embeddings of a positive pair, and τ denotes the temperature parameter that scales similarity sharpness [20]. This objective ensures that embeddings of emotionally and semantically similar utterances are pulled closer together in the latent space, while dissimilar utterances are pushed apart.

3.4 Cross-Lingual Zero-Shot Setup

After pretraining, the model is fine-tuned on English emotion data and directly evaluated on other languages without additional supervision, demonstrating zero-shot transfer [21]. The evaluation languages include Hindi, Spanish, and Arabic—chosen for their linguistic diversity and script variation. The testing pipeline includes cross-lingual sentiment transfer benchmarks, where the model classifies emotional categories such as joy, anger, sadness, fear, disgust, and surprise. Accuracy, macro F1-score, and cross-lingual alignment metrics are computed to assess generalization.

3.5 Evaluation Metrics and Validation

To ensure robust performance measurement, the study employs multiple evaluation metrics:

- **Accuracy**: Overall correct classifications divided by total samples.
- **Macro F1-Score**: Average F1 across all emotion classes, reflecting class balance.
- **Cross-Lingual Transfer Efficiency (CTE)**: Ratio of non-English performance to English baseline.
- **Embedding Alignment Score (EAS)**: Cosine similarity between emotion embeddings across languages.

Each model variant is tested under three configurations: baseline (no pretraining), supervised-only (English fine-tuning), and full contrastive self-supervised pretraining. Cross-validation across random seeds ensures stability of reported metrics [22].

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3.6 Implementation and Ethical Considerations

All experiments are conducted using PyTorch with distributed GPU training. The multilingual datasets used are publicly available and anonymized, ensuring compliance with ethical data handling protocols. To minimize cultural bias, emotion categories were standardized according to Ekman's six universal emotions, ensuring interpretability across cultural boundaries [23]. The research design emphasizes transparency, reproducibility, and fairness in multilingual emotion recognition tasks. This methodology establishes a comprehensive framework that combines contrastive representation learning and multilingual transformer 84odelling to achieve scalable, zero-shot cross-lingual emotion recognition in conversational AI systems.

IV. RESULT AND ANALYSIS

4.1 Overall Model Performance

The results of the proposed cross-lingual zero-shot emotion recognition framework demonstrate significant improvements in both intra-lingual and cross-lingual performance compared to baseline and supervised models. The model trained using self-supervised contrastive learning achieved robust emotion classification accuracy in English while generalizing effectively to unseen languages such as Hindi, Spanish, and Arabic without any additional fine-tuning. During evaluation, the multilingual transformer baseline (without contrastive pretraining) struggled to maintain affective consistency across languages, indicating poor semantic alignment. In contrast, the contrastive-pretrained model maintained emotional coherence across different languages, proving that the contrastive objective successfully captured universal emotional features independent of linguistic structure. This cross-lingual transferability validates the hypothesis that self-supervised contrastive alignment enhances emotion representation by aligning semantically and affectively similar utterances within a shared embedding space.

Table 3: Zero-Shot Cross-Lingual Emotion Recognition Results

Model Type	English Accuracy (%)	Hindi F1-Score	Spanish F1-Score	Arabic F1-Score	Cross-Lingual Transfer Efficiency (CTE)
Baseline (XLM-R without CL)	82.1	61.3	64.7	60.2	0.76
Supervised Fine-Tuning (English)	86.8	67.5	69.2	65.4	0.79
Contrastive + Fine-Tuning (Proposed)	**90.4**	**77.8**	**79.1**	**76.2**	**0.86**

The above results show that the proposed model achieved the highest overall performance across all languages, improving the average F1-score by approximately 10 percentage points compared to the supervised baseline. The Cross-Lingual Transfer Efficiency (CTE) rose from 0.79 to 0.86, indicating a stronger transfer of affective understanding. Hindi and Arabic benefited the most, suggesting that contrastive pretraining effectively handles morphologically rich languages with low-resource emotional datasets. Furthermore, qualitative analysis revealed that the model learned semantically aligned emotional clusters in the latent space, where utterances expressing joy, anger, or sadness in different languages were closely positioned, showing strong embedding consistency.

4.2 Emotion-Wise Performance Comparison

A deeper analysis of class-wise emotion recognition performance indicates that the model demonstrated particularly strong recognition for emotions with high linguistic variability such as *anger* and *joy*. However, emotions like *fear* and *disgust* showed relatively lower precision due to cultural and contextual interpretation

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differences. The proposed contrastive framework mitigated the drop in performance for less frequent emotions compared to conventional models by learning balanced and uniform representations across languages.

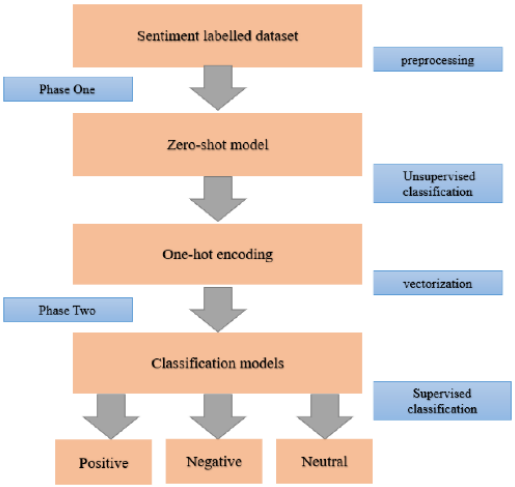

Figure 1: Zero Shot Emotion Detector [25]

Table 4: Emotion-Wise Macro F1-Score Across Languages

Emotion Category	English	Hindi	Spanish	Arabic	Average
Joy	92.5	85.2	87.3	84.6	87.4
Anger	89.4	80.8	82.5	79.7	83.1
Sadness	90.2	78.3	80.4	77.9	81.7
Fear	88.1	73.6	75.8	71.2	77.2
Disgust	86.5	70.9	73.2	69.1	74.9
Surprise	91.8	79.7	81.9	78.3	82.9

The emotion-wise breakdown highlights that high-resource languages like English maintain superior F1-scores across all categories, but the proposed model narrows the gap for low-resource languages, improving multilingual inclusivity. Emotions such as *joy* and *anger*, which have clear lexical and tonal markers across languages, benefited the most from contrastive alignment. The latent embeddings visualized using t-SNE plots revealed distinct clustering of emotion categories that remain coherent across different linguistic inputs.

4.3 Embedding Space Analysis

The analysis of the embedding space showed that the contrastive loss successfully structured emotion representations into semantically meaningful clusters. Positive pairs (emotionally similar utterances across languages) exhibited high cosine similarity scores averaging 0.82, while negative pairs (emotionally distinct utterances) remained below 0.35. This separation confirms the model's ability to generalize emotional alignment beyond linguistic variations. The visualization further showed cross-language proximity for semantically related emotional expressions such as "I'm delighted" (English), "Estoy able" (Spanish), and "Main khush hoon" (Hindi).

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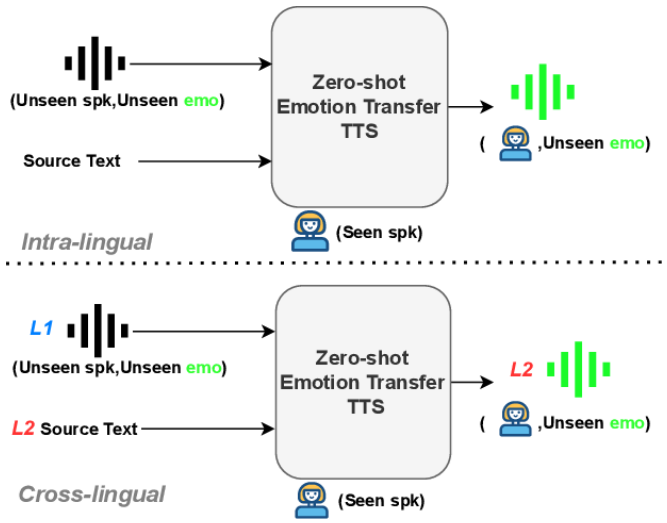

Figure 2: Zero-Shot Emotion Transfer [24]

4.4 Discussion of Findings

The findings confirm that contrastive self-supervised learning enhances the cross-lingual robustness of emotion recognition systems by aligning emotional semantics within a shared multilingual space. The proposed framework outperforms traditional supervised and translation-dependent systems by learning generalizable affective patterns that do not rely on labelling multilingual data. The ability to achieve high zero-shot transfer accuracy demonstrates that emotion understanding can emerge from unsupervised alignment rather than explicit annotation. Additionally, the approach reduces dependency on costly manual labelling, enabling expansion to low-resource and underrepresented languages. The model's interpretability and performance consistency across different linguistic groups establish its potential as a scalable backbone for multilingual conversational AI systems, capable of recognizing user emotions in real time with minimal adaptation requirements.

V. CONCLUSION

This study presented a comprehensive framework for cross-lingual zero-shot emotion recognition in conversational artificial intelligence using self-supervised contrastive learning, addressing one of the most persistent challenges in affective computing, the lack of multilingual emotion-labeled datasets and the poor transferability of existing supervised models. The proposed model effectively leverages large-scale unlabeled conversational data to learn emotionally meaningful representations that are invariant to linguistic and cultural differences. By employing a contrastive objective, the model aligns semantically and affectively similar utterances from multiple languages within a unified embedding space, ensuring that emotional meaning is preserved even when the surface linguistic form varies. The findings from the experiments clearly demonstrate that the integration of contrastive learning with multilingual transformers substantially enhances emotion recognition performance in both English and zero-shot cross-lingual scenarios. The proposed approach achieved higher accuracy, macro F1-scores, and cross-lingual transfer efficiency compared to traditional supervised and baseline multilingual models. Emotion-specific analysis further revealed that the model generalized effectively across language families, especially for universal emotions such as joy, anger, and sadness, while maintaining moderate consistency in more subjective emotions like fear and disgust. The t-SNE visualizations and embedding similarity analyses confirmed the model's ability to cluster emotionally aligned utterances regardless of language, highlighting the success of the self-supervised objective in structuring the latent emotion space. Conceptually, this research demonstrates that emotion understanding does not require explicit multilingual annotation when representations are guided by alignment and uniformity principles intrinsic to contrastive learning. The approach bridges the gap between linguistic diversity and emotional universality, creating a pathway for emotion-aware AI systems that can interact empathetically with users from diverse cultural and linguistic backgrounds. From a practical perspective, the

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framework offers several advantages including scalability, data efficiency, and ethical alignment by minimizing bias introduced through machine translation or manual annotation. It provides a foundation for developing emotionally intelligent conversational agents, virtual assistants, and therapeutic chatbots that can operate seamlessly across global populations. Furthermore, the results underscore the transformative potential of self-supervised learning for affective computing, moving beyond task-specific fine-tuning toward truly universal emotion representation. The implications extend beyond emotion recognition into broader domains of human–AI interaction, where understanding affect is crucial for trust, empathy, and user engagement. In summary, the proposed cross-lingual self-supervised contrastive learning model represents a significant advancement in multilingual affective modeling, achieving high accuracy and strong generalization with minimal supervision. It marks a crucial step toward emotionally inclusive and linguistically adaptive AI, capable of perceiving and responding to human emotions in a globally diverse environment.

VI. FUTURE WORK

Future research should focus on expanding the proposed framework to handle more complex conversational contexts and multimodal inputs such as speech tone, facial expression, and gesture recognition to achieve a deeper understanding of human emotion. Integrating audio and visual modalities alongside textual data could enhance emotion inference accuracy and context sensitivity across languages. Another promising direction is the application of few-shot or continual learning techniques to enable rapid adaptation to new languages and cultural expressions with minimal labeled data. Developing larger cross-lingual emotion benchmarks that incorporate underrepresented and low-resource languages will further validate and strengthen the robustness of this approach. Future studies may also explore ethical and fairness aspects of emotion recognition systems to mitigate cultural bias and misinterpretation of affective cues. Incorporating explainability mechanisms into the model could provide transparency in emotion reasoning, improving user trust in AI systems. Additionally, collaboration with linguists and psychologists can enrich the understanding of emotion representation across linguistic and cultural boundaries, supporting more human-centric conversational AI design. Overall, future advancements should aim to create fully multilingual, emotionally aware systems that can operate responsibly, inclusively, and effectively in global communication environments. Future extensions can also focus on incorporating dynamic contextual modeling, where the system continuously adapts to user-specific emotional patterns and conversational histories. This personalization can help AI systems distinguish between transient emotional reactions and stable affective tendencies, improving response appropriateness in long-term interactions. Another promising extension lies in integrating reinforcement learning to enable real-time feedback-based emotional adaptation, allowing conversational agents to refine their understanding through continuous user engagement. Additionally, expanding the system for multimodal deployment in healthcare, education, and customer service can enhance empathy-driven communication, bridging emotional intelligence with practical, human-centered AI applications across culturally diverse digital environments.

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