Behavioral Empathy Prediction in Dyadic Conversations with a Robot *** Supplementary Material ***

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I. Introduction

Our empathy definition: The definition of empathy is still heavily discussed in psychological literature [1], [2]. This has led to differing definitions for the same concept in affective computing applications [3], [4], [5], [6], [7]. The definition closer to the one we adopt in this work is based on conceptualizing empathy as a multi-dimensional [2], [1] and hierarchical [8], [9] construct.

In particular, we adopt the empathy definition based on a multi-disciplinary body of research in [2]. It presents 3 empathy dimensions, which are related to experiencing a similar emotional state in response to another person's (affective), understanding another person's affective state (cognitive), and acting in a manner that is consistent with those two previous dimensions (behavioral).

Affective empathy is considered the lowest form of empathy [9], [10], supplemented with cognitive elements to obtain the highest form of empathy.

Our empathy cues definition: Empathy cues have been used, but not explicitly named as a concept, in many affective computing applications. In the field of conversational artificial intelligence, empathy-related concepts like intent [11] or communication mechanisms [12] have been integrated into the generation pipeline to increase empathetic capabilities in such systems [13], [14], [15], [16], [17], [18], [19]. Likewise, empathy cues have found use in empathy prediction by incorporating elements like emotion recognition, emotional signals, and sentiment [20], [21].

Previous work by Lee et al. [22] has shown that empathy classifiers only consider surface-level details. Therefore, we wished to obtain insight by studying the influence of empathy cues in classification.

Empathy in HRI: Most works focus on studying the effects of having an empathetic robot in an HRI setting [23], [24], [25]. Besides, some works explore the impact of robot mediators that foster discussion in groups with empathetic communication [26].

Another study area is how empathetic humans are towards robots. Authors in [27] found that depending on the robot's behavior, and the rest of the humans in the group, children demonstrate different levels of empathy to the robot.

Designing EERobot: Our approach for a multi-modal dataset for empathy predictions in dyadic conversations is based on EmpatheticDialogues [28]. However, we were interested in the expression of empathy in the presence of a robot. We adapt the strategy of a *speaker* role presenting a situation in which they felt a given emotion. Then, a *listener* role responds to that utterance. The emotional contexts for each conversation are one of Plutchik's 8 main emotions [29]. Each speaker-listener pair explores 8 emotional contexts. This was to ensure diversity in responses. Likewise, we designed to have different levels of empathy by randomly assigning levels of familiarity between the participants. This is based on research that shows differences in empathy modulation due to familiarity [30]. This information was provided to the participants through an initial interjection by a social robot, ensuring that both participants were aware of the distinct factors to consider during the conversation.

There are significant limitations to our database. The main limiting factor is the lack of diversity among participants in the speaker role. Therefore, there might be biases introduced due to their demographic characteristics. Similarly, our emotional contexts are limited to higher-level emotions rather than those more fine-grained in EmpatheticDialogues.

On the other hand, we also tested our models in a real HRI scenario with groups of children. Their communication style differs from that of adults, and our robot actively mediates their interactions.

II. Implementation Details

Why we chose PBC4cip: It is designed to address class imbalance by computing weights for each class and using them alongside pattern support to perform classification. Its main advantage is that it is explainable and has outperformed others in empathy classification [20], [21]. We were interested in using this characteristic to study empathy classification in the context of HRI. However, the explainable capabilities of PBC4cip have been tied to the training set, which was of a different domain [20]. Therefore, we modify the algorithm to provide explainable information per individual inference. We name our implementation the contrast **P**attern-**B**ased **C**lassifier **for emp**athy (PBC4emp) and train it using a novel representation of just empathy cues in dyadic exchanges.

Besides, this classifier has already been proven to outperform classical machine-learning approaches for empathy classification [31], [20], [21]. Likewise, it is advantageous since it is explainable. This information is given in the form

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of the influence of each empathy cue per prediction, which would allow us to study their effects in the context of HRI. It receives as an input the empathy cues present in conversation exchanges.

Empathy annotation: We elected to use annotators over self-annotation to label the conversations since we focused on empathetic behavior displayed [2]. Similar research showed third-party annotation to be more reliable [20], [32]. We obtained empathy labels from two annotators with experience. They took the Empathy Quotient (EQ) questionnaire [33], [34] to ensure they did not present deficits in their empathetic abilities.

This questionnaire was developed to identify a lack of empathy as a feature of psychological conditions. As such, it is useful for measuring when a person is incapable of empathy using a single score [20]. The cut-off point for people with empathy deficits is 30 [33]. Our annotators presented a level of 52 and 63. Therefore, there was no reason to doubt their capabilities in identifying empathy. Annotators were then given our empathy definition alongside the levels of empathy and were familiarized with examples from a version of empathetic dialogues with verified empathy labels developed in [20]. They were instructed to label the display of empathy of the listener at the conversation level.

We present metrics of annotators against the final result consensus label in Table I.

TABLE I: Annotators original labeling against final consensus. CEM = closeness evaluation measure, and F1 = F1-score.

2-level					
Annotator	Accuracy	CEM	F1	Precision	Recall
First	0.831	-	0.832	0.837	0.831
Second	0.859	-	0.857	0.862	0.859
3-level					
Annotator	Accuracy	CEM	F1	Precision	Recall
First	0.677	0.788	0.665	0.657	0.677
Second	0.724	0.823	0.728	0.739	0.724

Thanks to this method, we obtained empathy labels for the EERobot dataset. Furthermore, we provide a baseline for classification by comparing the results to human labeling.

Changes in arousal and valence values: In Figure 1, we present violin plots of the arousal and valence values distribution from text and video sources, and after performing a weighted sum of both.

III. Prompts for GPT-4o

We include the prompts for GPT-4o used for benchmarking. The prompt presented is for classification using transcriptions, VA vectors, and pose mimicry.

Rate the behavioral empathy displayed by the listener per exchange. Our definition of empathy supports three dimensions in a hierarchical order: Affective, Cognitive, and Behavioral. Affective empathy means having emotional congruence with another person (same or similar emotion); Cognitive empathy is to understand the feelings and emotions of another and why they feel that way; Behavioral empathy is to communicate in a manner that demonstrates cognitive and affective empathy. Note that high empathy includes expressions of interest for the other person's emotional state or their situation.

Also consider the additional metrics we extracted from video: Arousal (range: -1 to 1): Reflects the level of emotional intensity of the speaker and listener, with -1 being very calm and 1 being highly aroused. Valence (range: -1 to 1): Indicates the emotional valence (positive or negative) of the speaker and listener, with -1 being very negative and 1 being very positive. Pose mimicry (binary: 1 or 0): Indicates whether the listener mimics the speaker's head movement (1 for yes, 0 for no).

Give your answer on this scale: 1 - little to no empathy, 2 - somewhat empathetic, and 3-empathetic.

An example of a pair of exchanges with empathy level 1: speaker: There was strange noise from the kitchen at night. listener: Did you have your alarm on speaker: Yes, but it didnt ring. I was spooked but it turned out I had left the window open and it was the wind. listener: Oh wow, I would have thought maybe an animal had gotten in.

An example of a pair of exchanges with empathy level 2: speaker: I was babysitting a few days ago and my cousin kept throwing her food on the floor. listener: That must have been frustrating. What did you do? speaker: I kept cleaning it up and put down a bunch of towels around her to protect the floor. I think it comes with the territory, she gets what she wants. listener: That made me laugh. And you are a great babysitter.

An example of a pair of exchanges with empathy level 3: speaker: My dad knew that I have recently hit a rough patch with my finances and gave me 2 grand. I cannot thank him enough. listener: How kind of him! I bet that is going to help you out a lot! speaker: It really is going to help a lot. I feel so blessed! listener: Dads are the best, what would we do without them?

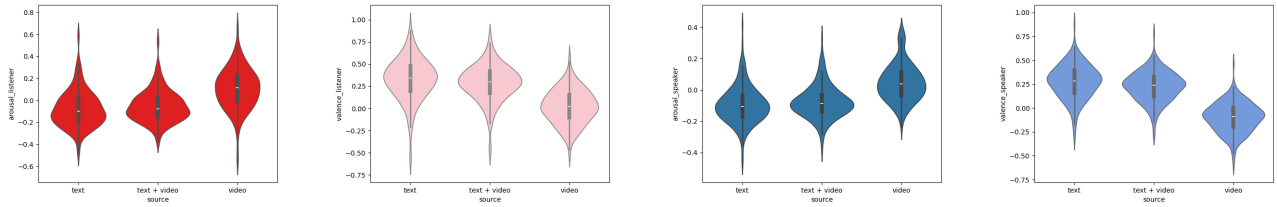
Answer format: Rate: ... Reason: ...

Other prompts used for this purpose had the following differences:

- Modified rating scale to be *Give your answer on this scale: 1 - no empathy, 2 - empathetic. .*
- Modified example with level 3 to have level 2 during binary classification.
- Eliminated the condition to consider additional metrics.

IV. Interpretability

Empathy cues ranking: In Figure 2, we present the ranking of cues. In Figure 3, we present the differences between the models that only use text against their counterparts that include video-based cues. The inclusion of video-based data changes the relevance of the cues for 2-level and 3-level classification. The biggest change is present in the listener's polarity response and the listener's emotional response. This shows that video-based cues alongside polarity and intent decrease the relevance of factors such as the explicit statement of an emotional reaction. Further work is necessary to study if this trend is present in larger datasets.



(a) listener arousal (b) listener valence (c) speaker arousal (d) speaker valence

Fig. 1: valence and arousal values for text, text and video, and video alone.

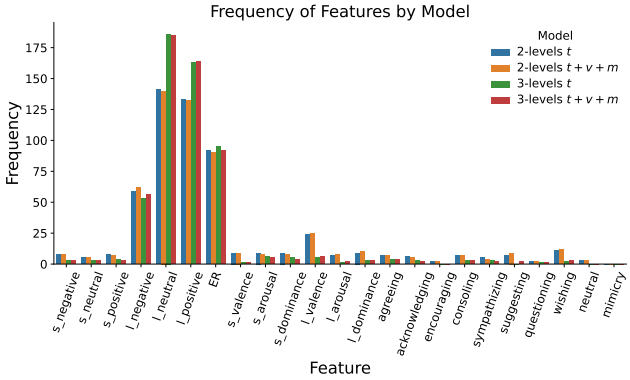


Fig. 2: Empathy cues ranking.

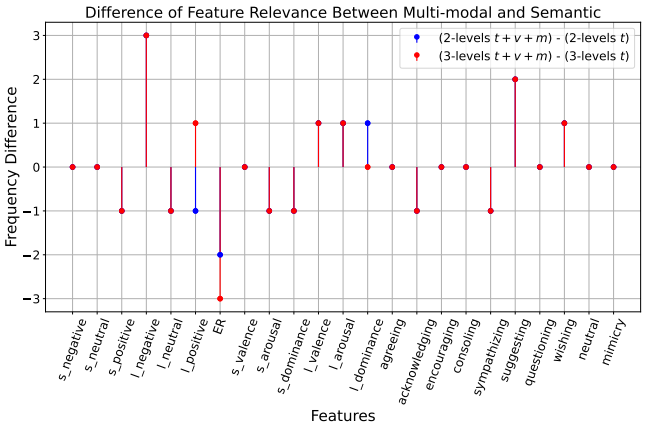


Fig. 3: Differences in the empathy cues rankings.

PBC4emp's explanations: In Table II, we see predictions for responses to two prompts. Alongside the predicted empathy level, the classifier provides interpretable information in the form of the top-3 most relevant cues for that prediction. This allows users to check whether the classification is correct. Furthermore, the cues can be used for additional purposes such as text generation using empathy-related concepts as is seen in [35] and [13].

GPT-4o's explanations: GPT-4o also provides explainable information. It provides natural language explanations for the prediction. These are quite useful for interpretations by users as well as ensuring that the predictions make sense. Nevertheless, these are not as useful for applications that use empathy cues. This is because GPT-4o doesn't have empathy cue models verified to be accurate. Likewise, the importance of each cue is not given using a verifiable metric, like our influence score. Therefore, the ranking and accuracy of the explanations are not immediately useful for other applications. Further work must be carried out to explore the advantages and disadvantages of both explainable approaches in different circumstances.

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TABLE II: Top 3 influential features of responses with different empathy levels. *L* = related to listener role and *S* = related to speaker role.

prompt	response	empathy level	top-3 features	top-3 features (L)	top-3 features (S)
"Does it bother you when your friends have all dates and you're single? It makes me feel inadequate"	"Yeah, you are "	1	l_word_len : 3 l_neutral : 0.55 s_word_len : 18	l_word_len : 3 l_neutral : 0.55 l_negative : 0.19	s_word_len : 18 s_negative : 0.90 dominance_speaker : -0.17
"Does it bother you when your friends have all dates and you're single? It makes me feel inadequate"	" Oh yeah, it bothers me a lot too!"	2	l_word_len : 8 l_negative : 0.93 l_neutral : 0.06	l_word_len : 8 l_negative : 0.93 l_neutral : 0.06	s_word_len : 18 s_neutral : 0.09 dominance_speaker : -0.17
"Does it bother you when your friends have all dates and you're single? It makes me feel inadequate"	"Yeah, it really sucks loneliness is no easy thing to go though"	3	l_word_len : 12 predictions_ER : 1 l_neutral : 0.04	l_word_len : 12 predictions_ER : 1 l_neutral : 0.04	s_word_len : 18 valence_speaker : 0.03 s_negative : 0.90
"I was so mad earlier someone hit my car and just drove off!"	"That's what you get haha!"	1	l_word_len : 5 acknowledging : 1.00 l_neutral : 0.25	l_word_len : 5 acknowledging : 1.00 l_neutral : 0.25	s_positive : 0.01 s_neutral : 0.04 s_word_len : 13
"I was so mad earlier someone hit my car and just drove off!"	"Was it a bad accident?"	2	l_word_len : 5 s_word_len : 13 l_neutral : 0.64	l_word_len : 5 l_neutral : 0.64 l_positive : 0.02	s_word_len : 13 s_neutral : 0.04 arousal_speaker : 0.29
"I was so mad earlier someone hit my car and just drove off!"	"Aww man, that's not ideal Did you get the plates?"	3	l_word_len : 10 l_neutral : 0.07 s_word_len : 13	l_word_len : 10 l_neutral : 0.07 l_positive : 0.00	s_word_len : 13 s_neutral : 0.04 s_positive : 0.01

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