Mixed Signals: Understanding Model Disagreement in Multimodal Empathy Detection

Anonymous ACL submission

Abstract

Multimodal models play a key role in empathy detection, but their performance can suffer when modalities provide conflicting cues. To understand these failures, we examine cases where unimodal and multimodal predictions diverge. Using fine-tuned models for text, audio, and video, along with a gated fusion model, we find that such disagreements often reflect underlying ambiguity, as evidenced by annotator uncertainty. Our analysis shows that dominant signals in one modality can mislead fusion when unsupported by others. We also observe that humans, like models, do not consistently benefit from multimodal input. These insights position disagreement as a useful diagnostic signal for identifying challenging examples and improving empathy system robustness.

1 Introduction

Empathy recognition in human communication is a nuanced and multifaceted task, and a core component of socially intelligent systems (Fung et al., 2016). Empathy, commonly defined as the capacity to understand others and share their emotional experiences, encompasses both cognitive perspective-taking and affective resonance (Baumeister and Vohs, 2007). In human interactions, language, speech, and visual cues jointly convey emotional intent (Holler and Levinson, 2019).

For AI systems, effectively interpreting these multimodal signals requires not only accurate unimodal representations but also robust integration of potentially conflicting information across modalities. Despite recent advances in multimodal emotion recognition (Jabeen et al., 2021), empathy recognition remains particularly complex, as empathy often arises from subtle contextual cues that may not align across modalities (Hasan et al., 2023). For example, a neutral utterance might be perceived as warm or concerned when accompanied by a sympathetic tone or expression.

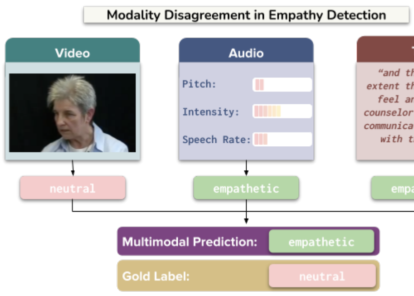

Figure 1: Given classifications provided by a single modality, we identify cases where integrating additional modalities leads to a different prediction. We analyze these flips to understand when and why they occur.

Our work investigates some of the complexities of multimodal empathy detection by examining instances of disagreement between multimodal models and their unimodal counterparts. In parallel, humans annotate unimodal and multimodal examples in our dataset for presence of empathy. Our analyses reveal that instances of multimodal and unimodal model disagreement often correspond to examples that are difficult for human annotators as well, highlighting regions of examples that are particularly challenging, ambiguous, or nuanced. By linking model modality disagreement to human disagreement, we offer new insight into the limitations of current empathy modeling and highlight the value of disagreement-based analysis in socially grounded language tasks.

2 Related Work

Empathy Modeling. Early computational work on empathy focused on generating emotionally relevant textual responses (Rashkin et al., 2019; Li et al., 2019), but these approaches are inherently limited by the absence of non-verbal cues critical to empathic understanding. Recent datasets such as EmpathicStories++ (Shen et al., 2024), MEDIC (Zhu et al., 2023), EMMI (Galland et al., 2024) and Chen et al. (2024) address this limitation by incorporating speech, facial expressions, and interaction context, enabling more comprehensive modeling of empathy. These resources have motivated frameworks like PEGS (Zhang et al., 2024), which integrate text and visual stickers for affective generation. Despite these advances, empathy remains difficult to model due to its reliance on subtle, often conflicting signals across modalities. Prior work has largely focused on improving fusion strategies under the assumption that modalities are complementary (Zadeh et al., 2017; Tsai et al., 2019), but has paid less attention to when fusion may fail or introduce noise.

Dataset Difficulty. Complementary lines of work have investigated data difficulty and model disagreement as tools for understanding model behavior. Swayamdipta et al. (2020) propose the dataset cartography method to identify hard or ambiguous training samples; Saha et al. (2022) demonstrate that difficult instances are also harder for both humans and models to explain; Wang et al. (2023)'s Learning-From-Disagreement (LFD) framework underscores the importance of examining disagreements between models to gain deeper, actionable insights into their behaviors.

Although ambiguity is intrinsic to empathy modeling, disagreement-based diagnostics remain underexplored; we leverage modality disagreement to flag difficult examples that both mislead fusion models and elicit annotator uncertainty.

3 Experiment 1: Identifying Complex Examples from Modality Disagreement

Disagreement between models trained on different modalities can reveal challenging, nuanced, or ambiguous examples. Here, we identify and analyze such cases of disagreement in binary empathy detection using a multimodal English empathy speech dataset collected from Youtube (Chen et al., 2024) (referred to as EMPSPEECH) consisting of 1,718 manually annotated English speech segments labeled as empathetic or neutral (Appendix A).

Experimental Setup. Examples in EMPSPEECH are comprised of video segments spanning three modalities: text (transcript), audio (speech), and video. The task is to predict whether the input contains empathetic (1) or neutral (0) speech.

We finetune two models per modality on the train set from EMPSPEECH: ROBERTA (Liu et al., 2019) and DEBERTA (He et al., 2021) for text, HUBERT (Hsu et al., 2021) and WAV2VEC2 (Baevski et al., 2020) for audio, and VIDEOMAE (Tong et al., 2022) and TIMESFORMER (Bertasius et al., 2021) for video (Appendix B.1).[1] Then, we extract embeddings from each best-performing unimodal model (ROBERTA, HUBERT, and VIDEOMAE, Table 1) to train a multimodal fusion model that projects all three modality embeddings into a shared latent space (Appendix B.2).

Modality	Model	Accuracy	F1
Text	**RoBERTa**	**0.75±0.02**	**0.73 ±0.02**
	DeBERTa	0.69±0.02	0.68±0.02
Audio	**HuBERT**	**0.72±0.01**	**0.71±0.01**
	Wav2Vec2	0.68±0.01	0.63±0.02
Video	**VideoMAE**	**0.77±0.02**	**0.77±0.02**
	TimesFormer	0.64±0.02	0.62±0.02
Fusion (All Modalities)		**0.76±0.02**	**0.72±0.02**

Table 1: Fine-tuned model performance by modality on empathy classification (mean ± std over five runs).

Results. We evaluate all models (unimodal and multimodal) on the test split of EMPSPEECH to identify *disagreements*, or examples where two models with varying input modalities assign different labels, highlighting cases where different modalities may carry ambiguous, conflicting, or modality-specific signals.

Text shows the highest disagreement with audio and video (Table 2), while audio and video align more closely; this likely reflects shared nonverbal cues such as prosody and facial expression. The fusion model's minimal disagreement with text suggests a bias toward verbal content, possibly mirroring annotators' own reliance on textual signals.

Figure 2 visualizes disagreement regions between each unimodal model and the fusion model. We plot unimodal confidence (x-axis) against fusion confidence (y-axis) in the correct label; hence confidence greater than 0.5 resulted in a correct prediction. This yields four quadrants: green (multimodal correct, unimodal incorrect), red (multimodal incorrect, unimodal correct), blue (both correct), and yellow (both incorrect). Red and green quadrants are disagreement regions which we explore to identify complex examples.

3.1 Modality-Based Feature Analysis

To better understand examples in disagreement regions, we extract and analyze modality-based human interpretable features.

[1]The hidden layer dimensions of all models we consider are similar.

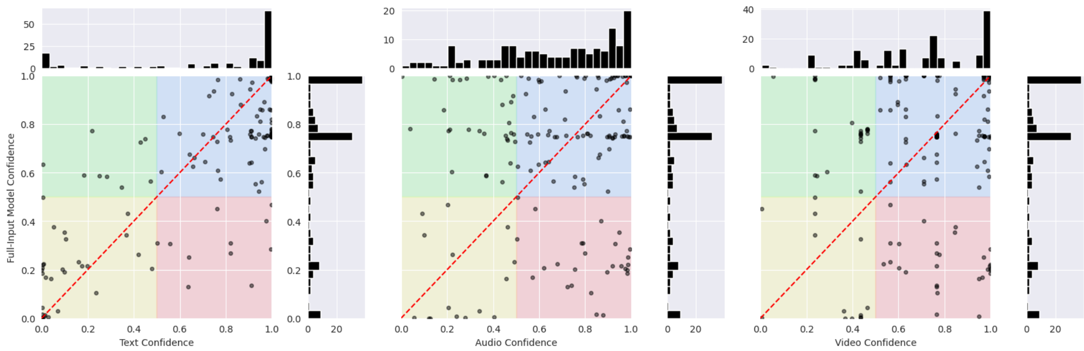

Figure 2: Comparing predictions between unimodal (text, audio, video) and multimodal models. We highlight regions where model predictions *agree* (blue and yellow quadrants) and disagree (red and green quadrants).

Modality	Text	Audio	Video
Text	–	0.338	0.318
Audio	0.338	–	0.253
Video	0.318	0.253	–
Full	0.214	0.383	0.331

Table 2: Pairwise disagreement rates among unimodal models and the fusion model, computed as the fraction of test examples with differing predictions.

Feature	**Red vs. Blue**		**Green vs. Blue**	
	p-value	Direction	p-value	Direction
valence	**0.0047**	$\mu_{\textbf{blue}} > \mu_{\textbf{red}}$	0.5166	$\mu_{\text{green}} > \mu_{\text{blue}}$
arousal	**0.0065**	$\mu_{\textbf{blue}} > \mu_{\textbf{red}}$	**0.0136**	$\mu_{\textbf{blue}} > \mu_{\textbf{green}}$
Mean Pitch	**0.0100**	$\mu_{\textbf{blue}} > \mu_{\textbf{red}}$	**0.0001**	$\mu_{\textbf{blue}} > \mu_{\textbf{green}}$
dominance	**0.0108**	$\mu_{\textbf{blue}} > \mu_{\textbf{red}}$	0.0667	$\mu_{\text{blue}} > \mu_{\text{green}}$
Min Pitch	**0.0333**	$\mu_{\textbf{blue}} > \mu_{\textbf{red}}$	**0.0001**	$\mu_{\textbf{blue}} > \mu_{\textbf{green}}$
Jitter	**0.0347**	$\mu_{\textbf{red}} > \mu_{\textbf{blue}}$	0.0667	$\mu_{\text{green}} > \mu_{\text{blue}}$
Max Intensity	0.1260	$\mu_{\text{red}} > \mu_{\text{blue}}$	**0.0023**	$\mu_{\textbf{green}} > \mu_{\textbf{blue}}$

Table 3: T-test results comparing red vs. blue and green vs. blue examples for audio features with $\alpha = 0.05$. Statistically significant results are bolded. See Appendix D for full table.

Audio. We extract 12 prosodic and paralinguistic features from audio signals: 9 low-level acoustic features using PRAAT (Boersma and Weenink, 1992–2022) and PARSELMOUTH (Jadoul et al., 2018), and 3 high-level affective dimensions—valence, arousal, and dominance—using a finetuned WAV2VEC2 (Wagner et al., 2023). We compare feature distributions using t-tests for examples in disagreement quadrants (red and green) compared to those in the blue quadrant, signifying a non-ambiguous, easy examples. Blue examples have several significantly elevated pitch-related values than red examples (Table 3), suggesting that stronger prosodic fluctuations are frequently corroborated by other modalities. Examples in the green quadrant show significantly higher *Max Intensity* than in blue, potentially reflecting the role of volume-based emphasis in aiding unimodal predictions. Both red and green examples exhibit significantly lower arousal than blue examples, suggesting that these less-aroused, subtler examples lack sufficient affective intensity, which misleads both unimodal and multimodal models.

AU	p (R vs B)	Dir	p (G vs B)	Direction
AU04	**0.0106**	**red** > **blue**	0.3682	green > blue
AU12	**0.0174**	**blue** > **red**	0.8977	green > blue
AU05	0.1837	blue > red	**<0.0001**	**blue** > **green**

Table 4: T-test results comparing AU activation rates between red vs. blue and green vs. blue with $\alpha = 0.05$. Statistically significant results are bolded. See Appendix D for full table

Video. We examine facial action unit (AU) activations (Baltrušaitis et al., 2016) from video. AU04 (Brow Lowerer), AU12 (Lip Corner Puller), and AU05 (Upper Lid Raiser) show significant differences across example types, revealing how specific facial expressions contribute to perceptual ambiguity (Table 4). AU04 is more active in red examples than blue, indicating that despite its visually strong presence, its signal conflicts with other modalities. In contrast, AU12, associated with positive affect, and AU05, which is linked to attentiveness (Friesen and Ekman, 1978), both show greater activation in blue examples than in red and green, respectively, suggesting that these expressions may serve as clearer cues that are more consistently interpreted across modalities. Our findings indicate that fine-grained facial signals may contribute to perceptual complexity in the visual stream.

Text. Visualizing UMAP (Sainburg et al., 2021) projections of text embeddings (Figure 3) reveals that examples in disagreement regions (red and green) tend to cluster along the boundary between consistently correct (blue) and consistently incor-

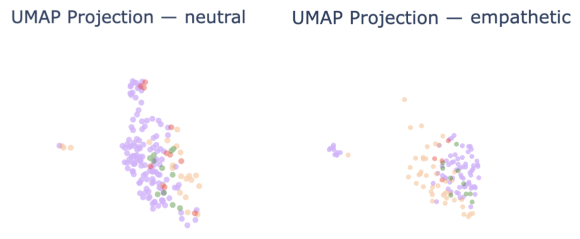

Figure 3: UMAP of text-only embeddings for empathetic (left) vs. neutral (right) examples, colored by modality disagreement; red and green points cluster near the decision boundary, marking ambiguous cases.

Quadrant	Unimodal Judgment	Multimodal Judgment	Δ
Red	0.301	0.164	-0.137
Blue	0.379	0.646	0.267
Yellow	0.225	0.329	0.104
Green	0.482	0.218	-0.264

Table 5: Cohen's Kappa between internal and external annotators, computed separately for each quadrant and prediction round.

rect (yellow) examples. Rather than forming isolated clusters, disagreement examples occupy transition zones in the embedding space — areas where semantic cues are weak. This underscores that red and green examples are ambiguous and confirms modality disagreement as a reliable marker of challenging examples in empathy detection.

4 Experiment 2: Characterizing Complex Examples

We further assess whether model disagreements stem from data ambiguity via a human annotation study that tests if disagreement examples are equally challenging for annotators.

Annotation Setup. We sample 204 examples evenly split across the four quadrants of each Figure 2 modality plot. For each example, annotators provide a binary judgment (empathetic or neutral) from a unimodal signal, then a judgment from the full multimodal version (instructions in Appendix C), allowing us to track how human predictions shift with additional modality signals and understand the cognitive burden of multimodal integration. All examples were annotated by one author and one external annotator. Table 12 in the Appendix showcases frames and transcripts for four examples, along with annotator judgments.

Results. Annotator *disagreement*, measured with Cohen's Kappa (Cohen, 1960), can signal complex phenomena in examples (Jiang and de Marneffe, 2022; Pavlick and Kwiatkowski, 2019) such as uncertainty in meaning leading to discrepancies in reasoning. In disagreement regions (red and green), we see a *decrease* in annotator agreement between unimodal and multimodal judgments (Table 5), indicating that humans diverge when weighing signals across modalities. In contrast, annotator agreement *improves* on examples where unimodal and multimodal model predictions are in agreement, supporting our hypothesis that these examples are relatively unambiguous and reliably interpreted once the full context is available (Table 5). This pattern persists even when we restrict to longer utterances ($\geq$ 6 tokens, the dataset median), which shows the same drop in κ (Appendix F). These results collectively corroborate our hypothesis that modality disagreement can serve as a valuable signal for identifying ambiguous, challenging, or complex instances that are also difficult for human annotators.

5 Discussion and Conclusion

We have demonstrated how disagreement, both between modalities and between humans and models, can serve as a diagnostic lens to understand the complexity of multimodal empathy detection, challenging the assumption that more signal from other modalities reliably yields better performance. Our analysis reveals that disagreement between unimodal and multimodal models is often not arbitrary, but instead marks the presence of subtle, ambiguous, or context-sensitive cues that challenge fusion models and human annotators alike. While our study focuses on speaker-centric empathy (evaluating speakers' empathic expression), our diagnostic can be generalized to listener-centric tasks, which dominate existing empathy datasets and capture listeners' emotional responses to each utterance (Appendix A.2). These findings emphasize the necessity of high-quality annotation in socially complex tasks like empathy detection, where model errors may reflect genuine human uncertainty. This framework provides a scalable method for identifying ambiguity and enhancing model reliability, especially in recognizing complex emotional states that involve inherent disagreement and uncertainty. Our work lays the foundation for several directions of future work, such as creating adversarial test sets to evaluate empathy detection systems in realistic scenarios or the identification of challenging examples for human annotation in an active learning setup to improve model robustness.

Limitations

We acknowledge several limitations in our study. Our analyses are based on a limited dataset and a small number of human annotators. Given that empathy is inherently subjective, annotations may vary due to individual interpretations, potentially introducing biases rather than reflecting universal properties of the data. Additionally, we rely on a single dataset, and future work should investigate whether the patterns we observe hold across other datasets and domains.

Our data is also derived from U.S.-based, English-language television and interview content. As such, the generalizability of our findings to multilingual or culturally diverse settings may be limited. Future research should investigate these patterns in varied cultural and linguistic environments to better assess the broader applicability of our conclusions.

Ethics Statement

We use a publicly available dataset and strictly use open-source models for analysis.

All annotations were conducted by an author and an individual affiliated with the research team. No participants were recruited via crowdsourcing or external platforms, and no monetary compensation was provided, as the annotators were contributing in a research capacity. We provide detailed information on what we ask the annotators to annotate and how we plan to use the data. The annotators willingly agreed to participate with full knowledge of the task. No sensitive or identifying information were collected from annotators.

We note that empathy expression may vary across cultures, and our findings may not generalize to non-English or non-Western contexts. We encourage future work to explore these questions in more diverse settings.

We will release all code and experimental resources at `https://anonymous.4open.science/r/multimodal-empathy-disagreement-F48B` to support reproducibility.

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A Dataset

A.1 Dataset Specifications

We use a multimodal empathy dataset (Chen et al., 2024) consisting of 346 English-language videos totaling approximately 53 hours, collected from YouTube between 2020 and 2022 using keywords like "empathy" and "empathetic training." The dataset includes empathy training sessions, therapy roleplays, interviews, TED Talks, and TV/movie scenes, comprising both acted (62%) and spontaneous (38%) speech. Each video was labeled by at least three expert annotators as either empathetic or neutral, with final labels determined by majority vote. Metadata such as speaker gender, topic, and emotional context was manually annotated, covering themes like therapy, parenting, workplace dynamics, and social relationships. From this collection, a subset of 65 videos was transcribed, diarized, and manually re-aligned using Praat to ensure accurate speaker segmentation and time alignment. This process resulted in 1,718 annotated segments with speaker labels, timestamps, transcripts, and empathy stage annotations, enabling fine-grained analysis of empathy in naturalistic and semi-scripted settings.

A.2 Dataset Comparison

To the best of our knowledge, our work is the first to evaluate multimodal disagreement on speaker-centric empathy detection datasets. Most publicly available empathy datasets (such as EMPATHICSTORIES++ (Shen et al., 2024) and OMG-EMPATHY (Barros et al., 2019)) are fundamentally structured around listener response, not speaker expression. In these datasets, the task is to predict how empathetic a listener feels after hearing a story, rather than to assess whether the speaker themselves is expressing empathy. For instance, in EMPATHICSTORIES++, participants record personal stories and then rate their own emotional responses, framing empathy as a *reaction* to the content rather than as a property of the speaker's delivery. Similarly, OMG-EMPATHY evaluates listener self-reported affective states following brief monologues, again focusing on perceived empathy rather than expressed empathy. This distinction matters because listener-focused tasks inherently entangle speaker behavior with listener subjectivity, making it difficult to isolate which cues (textual, audial, or visual) are directly responsible for empathy expression. In contrast, the dataset we use in this study (Chen et al., 2024) is one of the only accessible resources that explicitly asks annotators to evaluate the *speaker's* empathy, based solely on the speech segment itself, across modalities. This framing allows us to analyze how empathy is expressed in real time by the speaker, independent of listener interpretation, and enables direct comparisons between modalities on their ability to convey empathetic intent. Our current dataset offers a uniquely valuable lens into the structure of empathy as a speaker-side communicative behavior: something that remains underexplored in the literature. In future work, our modality-disagreement diagnostic could be used to flag nuanced, high-ambiguity segments that challenge *listener* empathy models. They could serve as an effective proxy for identifying segments that elicit high listener variance in empathy judgments, enabling targeted annotation and model refinement on exactly those ambiguous utterances where listener-centric prediction systems struggle most.

B Model Training Details

Data was split into train, test and validation sets using random sampling, with an 80-10-10 split. We run fine-tuning and inference for all open-source models on an A100 GPU in Google Colab.

B.1 Unimodal Model Training Details

Each model is trained on a binary empathy classification task using precomputed 768-dimensional embeddings. We freeze all but the final two transformer layers and train for 15 epochs with a learning rate of 5e-6 and batch size of 8.

B.2 Fusion Model Details

Each unimodal model representation is independently gated and passed through an attention mechanism that computes modality-specific weights. The weighted embeddings are aggregated and classified using a three-layer feedforward network with max pooling. The fusion model is trained for 10 epochs using a learning rate of 1e-4 and includes modality dropout during training. To characterize how the model balances each of the three modalities at inference time, we computed the per-modality gate-weight distributions over the full test set (Table 6). The mean gate weights indicate that our model allocates substantial importance to each modality, with only a slight preference toward audio and video. The high variance also shows that the model dynamically adapts its reliance on each modality on a per-sample basis. Thus, our fusion model draws substantially on all three streams; no single modality is systematically favored.

Modality	Mean	Standard Deviation
Text	0.430	0.297
Audio	0.502	0.227
Video	0.476	0.315

Table 6: Per-modality gate-weight distributions over the full test set.

C Annotation Instructions

We employed two annotators, one of the paper's authors and an non-author, both fluent English speakers based in the United States. No additional demographic information was collected, as the annotation was conducted internally for research purposes.

Annotators were asked to provide two judgments per example, labeling each as either empathetic or neutral (Figure 4). A excerpt describing empathy (drawn from the Encyclopedia of Social Psychology, Volume 1, (Baumeister and Vohs, 2007)) was provided to ensure a consistent conceptual foundation for annotation:

> Empathy is often defined as understanding another person's experience by imagining oneself in that other person's situation: One understands the other person's experience as if it were being experienced by the self, but without the self actually experiencing it. There are three commonly studied components of emotional empathy. The first is feeling the same emotion as another person (sometimes attributed to emotional contagion, e.g., unconsciously "catching" someone else's tears and feeling sad oneself). The second component, personal distress, refers to one's own feelings of distress in response to perceiving another's plight. The third emotional component, feeling compassion for another person, is the one most frequently associated with the study of empathy. Cognitive empathy refers to the extent to which we perceive or have evidence that we have successfully guessed someone else's thoughts and feelings.

Annotators were given an annotation flag indicating which modality to use for the first pass; for instance, if the flag was text, only the transcript was to be used to make the first prediction. After submitting the first judgment, annotators were then given access to the full video, including all available audio, visual, and textual information. They were then asked to provide a second prediction.

D Full Feature Comparisons

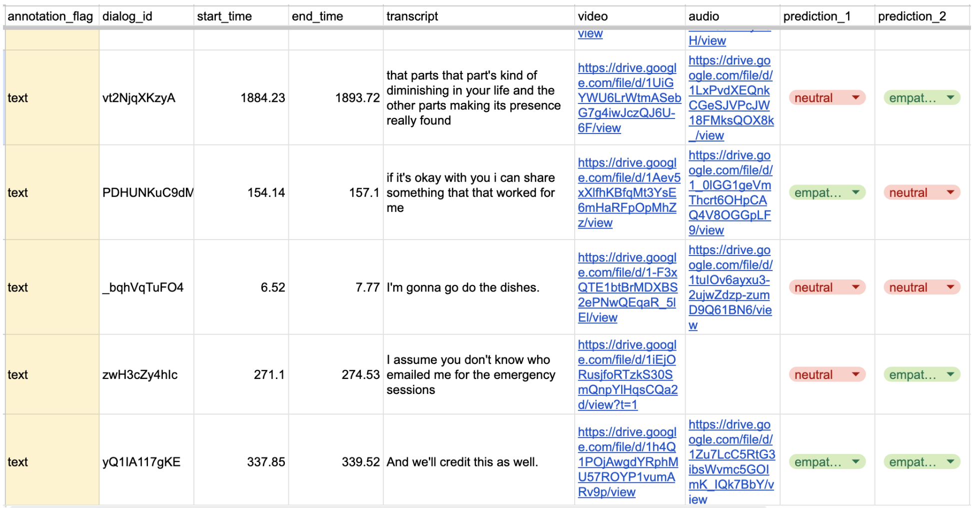
Tables 7, 9 and 10 provide additional results from the t-tests comparing examples across different confidence quadrants. Table 7 provides an internal comparison between the disagreement quadrants. Table 9 presents the full version of the audio feature comparisons summarized in Table 3. Table 10 expands on the facial feature comparisons shown in Table 4.

E Feature Distributions

Figures 5 and 6 visualize the distributions of key features across confidence quadrants. Figure 5 presents the distribution of selected audio features (e.g., pitch, intensity) for red, green, and blue examples, highlighting acoustic patterns associated with model disagreement. Figure 6 shows activation rates for facial Action Units (AUs) in red, green, and blue examples, illustrating how specific facial expressions vary across agreement conditions. These visualizations complement the statistical comparisons reported in Tables 9 and 10, providing a more interpretable view of the underlying feature dynamics.

F Annotator Disagreement for Longer Utterances

In order to verify that transcript length is not driving our disagreement effect, we repeated the Cohen's κ analysis on the subset of clips containing at least six tokens (the dataset median). Table 11 shows example utterances below and above the median; examples below the median often include short phrases and backchannels, while examples above the median are often complete sentences with richer lexical and syntactic structure. As shown in Table 8, the red and green quadrants continue to exhibit substantial drops in κ compared to the blue and yellow quadrants, which exhibit substantial gains with additional information.



annotation_flag	dialog_id	start_time	end_time	transcript	video	audio	prediction_1	prediction_2
					view	H/view		
text	vt2NjqXKzyA	1884.23	1893.72	that parts that part's kind of diminishing in your life and the other parts making its presence really found	https://drive.google.com/file/d/1UiGYWU6LrWtmASebG7g4iwJczQJ6U-6F/view	https://drive.google.com/file/d/1LxPvdXEQnkCGeSJVPcJW18FMksQOX8k_/view	neutral	empat…
text	PDHUNKuC9dM	154.14	157.1	if it's okay with you i can share something that that worked for me	https://drive.google.com/file/d/1Aev5xXlfhKBfqMt3YsE6mHaRFpOpMhZz/view	https://drive.google.com/file/d/1_0lGG1geVmThcrt6OHpCAQ4V8OGGpLF9/view	empat…	neutral
text	_bqhVqTuFO4	6.52	7.77	I'm gonna go do the dishes.	https://drive.google.com/file/d/1-F3xQTE1btBrMDXBS2ePNwQEqaR_5lEl/view	https://drive.google.com/file/d/1tulOv6ayxu3-2ujwZdzp-zumD9Q61BN6/view	neutral	neutral
text	zwH3cZy4hlc	271.1	274.53	I assume you don't know who emailed me for the emergency sessions	https://drive.google.com/file/d/1iEjORusjfoRTzkS30SmQnpYlHqsCQa2d/view?t=1		neutral	empat…
text	yQ1IA117gKE	337.85	339.52	And we'll credit this as well.	https://drive.google.com/file/d/1h4Q1POjAwgdYRphMU57ROYP1vumARv9p/view	https://drive.google.com/file/d/1Zu7LcC5RtG3ibsWvmc5GOImK_IQk7BbY/view	empat…	empat…

Figure 4: Annotation interface

Feature	t-stat	p-value	Mean Comparison
Mean Pitch	**2.453**	**0.0159**	$\boldsymbol{\mu_{\text{red}} > \mu_{\text{green}}}$
Max Intensity	**-2.124**	**0.0366**	$\boldsymbol{\mu_{\text{green}} > \mu_{\text{red}}}$
Max Pitch	**2.016**	**0.0465**	$\boldsymbol{\mu_{\text{red}} > \mu_{\text{green}}}$
Min Pitch	**2.007**	**0.0475**	$\boldsymbol{\mu_{\text{red}} > \mu_{\text{green}}}$
valence	-1.908	0.0593	$\mu_{\text{green}} > \mu_{\text{red}}$
arousal	1.827	0.0705	$\mu_{\text{red}} > \mu_{\text{green}}$
speaking_rate	1.773	0.0807	$\mu_{\text{red}} > \mu_{\text{green}}$
dominance	1.712	0.0899	$\mu_{\text{red}} > \mu_{\text{green}}$
Shimmer	0.773	0.4416	$\mu_{\text{red}} > \mu_{\text{green}}$
Jitter	0.622	0.5355	$\mu_{\text{red}} > \mu_{\text{green}}$
Mean Intensity	0.544	0.5886	$\mu_{\text{red}} > \mu_{\text{green}}$
HNR	0.508	0.6129	$\mu_{\text{red}} > \mu_{\text{green}}$
Min Intensity	-0.429	0.6685	$\mu_{\text{green}} > \mu_{\text{red}}$

Table 7: T-test results comparing audio features between red and green examples. Statistically significant results are bolded.

Quadrant	Unimodal Judgment	Multimodal Judgment	Δ
Red	0.347	0.143	-0.204
Blue	0.364	0.533	0.169
Yellow	0.304	0.548	0.244
Green	0.573	0.329	-0.244

Table 8: Cohen's Kappa between internal and external annotators for examples of at least six tokens (the dataset median), computed separately for each quadrant and prediction round.

Feature	p (Red vs Blue)	Direction	p (Green vs Blue)	Direction
valence	**0.0047**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{red}}$	0.5166	$\mu_{\text{green}} > \mu_{\text{blue}}$
arousal	**0.0065**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{red}}$	**0.0136**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{green}}$
Mean Pitch	**0.0100**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{red}}$	**0.0001**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{green}}$
dominance	**0.0108**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{red}}$	0.0667	$\mu_{\text{blue}} > \mu_{\text{green}}$
Min Pitch	**0.0333**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{red}}$	**0.0001**	$\boldsymbol{\mu}_{\text{blue}} > \boldsymbol{\mu}_{\text{green}}$
Jitter	**0.0347**	$\boldsymbol{\mu}_{\text{red}} > \boldsymbol{\mu}_{\text{blue}}$	0.0667	$\mu_{\text{green}} > \mu_{\text{blue}}$
Max Intensity	0.1260	$\mu_{\text{red}} > \mu_{\text{blue}}$	**0.0023**	$\boldsymbol{\mu}_{\text{green}} > \boldsymbol{\mu}_{\text{blue}}$
Mean Intensity	0.1599	$\mu_{\text{red}} > \mu_{\text{blue}}$	0.5329	$\mu_{\text{blue}} > \mu_{\text{green}}$
HNR	0.2217	$\mu_{\text{blue}} > \mu_{\text{red}}$	0.2055	$\mu_{\text{blue}} > \mu_{\text{green}}$
speaking_rate	0.2723	$\mu_{\text{blue}} > \mu_{\text{red}}$	0.9991	$\mu_{\text{green}} > \mu_{\text{blue}}$
Shimmer	0.4122	$\mu_{\text{red}} > \mu_{\text{blue}}$	0.1541	$\mu_{\text{blue}} > \mu_{\text{green}}$
Max Pitch	0.6845	$\mu_{\text{red}} > \mu_{\text{blue}}$	0.2647	$\mu_{\text{blue}} > \mu_{\text{green}}$
Min Intensity	0.7999	$\mu_{\text{blue}} > \mu_{\text{red}}$	0.1571	$\mu_{\text{blue}} > \mu_{\text{green}}$

Table 9: T-test results comparing audio features between red vs. blue and green vs. blue examples. Statistically significant p-values are bolded.

AU	p (Red vs Blue)	Direction	p (Green vs Blue)	Direction
AU04: Brow Lowerer	**0.0106**	**red > blue**	0.3682	green > blue
AU12: Lip Corner Puller	**0.0174**	**blue > red**	0.8977	green > blue
AU05: Upper Lid Raiser	0.1837	blue > red	**<0.0001**	**blue > green**
AU17: Chin Raiser	0.2256	red > blue	0.9802	blue > green
AU10: Upper Lip Raiser	0.2275	blue > red	0.6700	green > blue
AU45: Blink	0.3200	blue > red	0.7462	green > blue
AU07: Lid Tightener	0.3252	blue > red	0.9318	blue > green
AU14: Dimpler	0.4593	red > blue	0.0652	green > blue
AU20: Lip Stretcher	0.5701	blue > red	0.7907	blue > green
AU09: Nose Wrinkler	0.6211	blue > red	0.7639	green > blue
AU25: Lips Part	0.6227	blue > red	0.7492	blue > green
AU01: Inner Brow Raiser	0.6529	blue > red	0.4674	green > blue
AU23: Lip Tightener	0.6630	red > blue	0.3474	green > blue
AU28: Lip Suck	0.6735	red > blue	0.9846	green > blue
AU26: Jaw Drop	0.6851	red > blue	0.4596	blue > green
AU06: Cheek Raiser	0.7097	blue > red	0.3201	green > blue
AU15: Lip Corner Depressor	0.9528	red > blue	0.4834	green > blue
AU02: Outer Brow Raiser	0.9647	blue > red	0.6677	green > blue

Table 10: T-test results comparing AU activation rates between red vs. blue and green vs. blue. Bolded p-values are statistically significant.

< 6 Tokens	$\geq$ 6 Tokens
"there's no way" (3 tokens)	*"No, no he's a good guy go easy on him he's lost his son, Fabio"* (15 tokens)
"You lost it?" (3 tokens)	*"You kids have the biggest hearts I've ever seen."* (9 tokens)
"I can understand that." (4 tokens)	*"congrats my dude, on everything man"* (6 tokens)

Table 11: Example utterances with fewer than six tokens (left) versus at least six tokens (right).

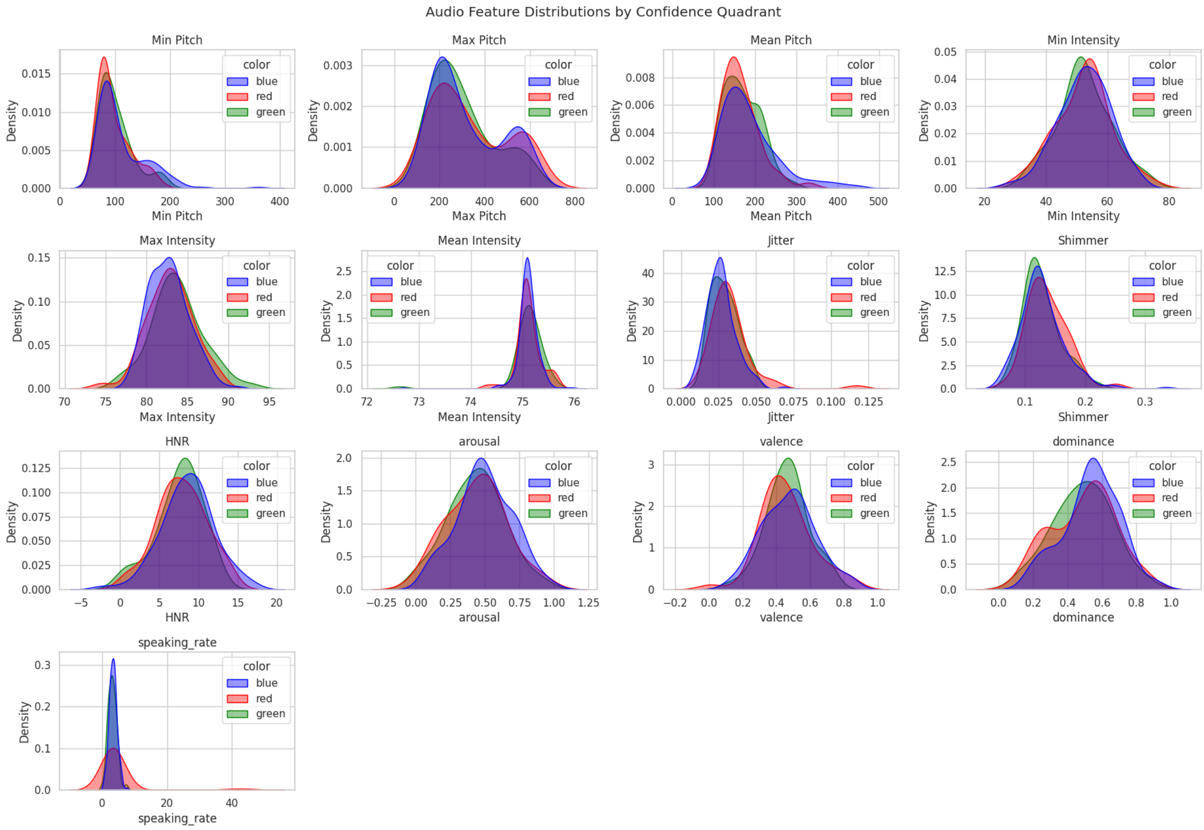


Figure 5: Distribution of audio features for red, green and blue examples across the confidence quadrants. Red examples are those correctly classified by the unimodal audio model but misclassified by the multimodal model; green examples represent the reverse. Blue examples represent those correctly classified by both the unimodal audio model and the multimodal model. Significant differences appear in pitch and intensity-based features.

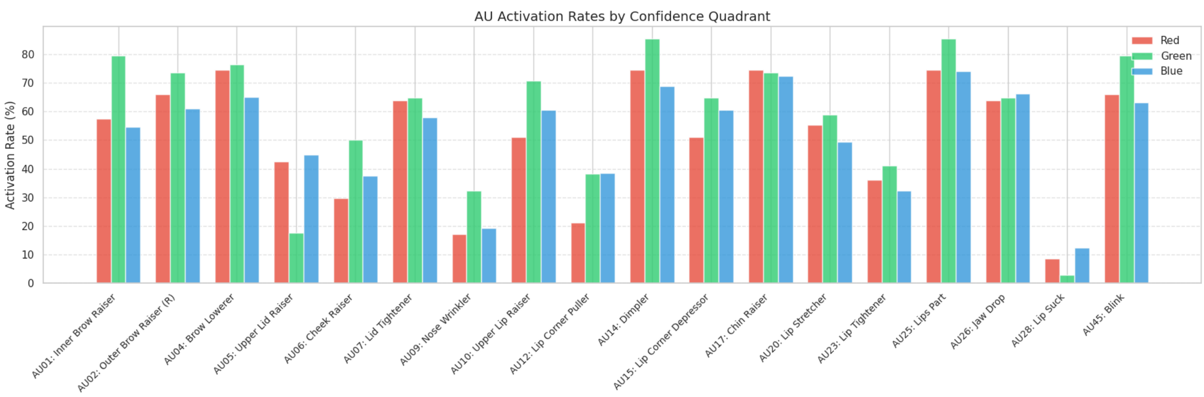


Figure 6: AU activation rates for red, green, and blue examples. Red bars indicate examples where the unimodal visual model predicted correctly but the multimodal model did not (Red: Unimodal > 0.5, Multimodal < 0.5). Green bars show the reverse. Blue bars indicate examples where both the unimodal and multimodal models correctly predicted the label.

 **Transcript:** "I assume you don't know who emailed me for the emergency sessions" **Quadrant:** Red **True Label:** Empathetic **Annotator 1:** Neutral **Annotator 2:** Empathetic	 **Transcript:** "In fact research suggests we spend about 55 percent of our day..." **Quadrant:** Blue **True Label:** Neutral **Annotator 1:** Neutral **Annotator 2:** Neutral
 **Transcript:** "One of the reasons I wanted to come here tonight was to discuss our future." **Quadrant:** Yellow **True Label:** Neutral **Annotator 1:** Empathetic **Annotator 2:** Empathetic	 **Transcript:** "It's good to have you here um especially to talk about a topic that i think is one of the more sensitive topics that we we're discussing in society today..." **Quadrant:** Green **True Label:** Empathetic **Annotator 1:** Neutral **Annotator 2:** Empathetic

Table 12: Example clips from each disagreement quadrant with transcript and labels.