Computational Linguistic Approach to Empathy and its Language Communication Pattern

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Abstract

Research on empathy computation within the context of disaster narratives is the primary focus of this study. We aim to model the emotional dimensions of empathy while systematically exploring its cognitive and social aspects through linguistic features. By analyzing empathy in social media data, we provide a theory-grounded account of its communication patterns, drawing on principles of embodiment and trust concerning social behaviors. Findings reveal that individuals with higher levels of empathy are more likely to use concrete language to convey intentions that foster connection and broader social engagement. Our work demonstrates how language, emotion, and social cognition interact, offering a computational investigation of empathy that may contribute to new perspectives in language technology and communication.

1 Introduction

Empathy, as a significant aspect of human communication, is a complex socio-emotional behavior concerning how we understand others. It interacts with advanced cognitive processes (Coplan and Goldie, 2011; Omdahl, 1995), yet can be effectively conveyed through linguistic devices.

However, over two decades after Picard (1997)'s seminal work on Affective Computing, conceptualizing and measuring empathy remains challenging. On one hand, previous studies have focused mostly on empathy's emotional dimension, while broader facets (e.g., cognitive reasoning and interpersonal tendencies) leave scope for further inquiry. On the other hand, while benefiting from the progress of large language models (LLMs), empathetic modeling remains confined to tasks such as detection and response generation in two-person counseling settings, lacking theoretical interpretability of its linguistic communication patterns at scale.

Motivated by these gaps, our goal is to broaden the boundary of understanding empathy, extract its linguistic representations, and thereby enhance empathic modeling accuracy. Specifically, we developed a replicable language-anchored method using natural language processing technology to compare linguistic differences between empathic and non-empathic expressions in digital contexts. Our key contributions are as follows:

- We propose a theory-grounded body-cognition framework to guide linguistic feature design for empathy modeling.
- We improve empathy classification performance by integrating cognitive, perceptual,and syntactic features.
- We draw on principles of embodiment and trust to account for the communication patterns of empathy.

2 Theoretical Framework

Integrating emotional, cognitive, and social perspectives, we introduced two key theories: the Stereotype Content Model (SCM) (Fiske et al., 2002) and Embodied Appraisal Theory (EAT) (Prinz, 2004).

SCM identifies *Warmth* (refined into *Trust* and *Sociability*) (Abele and Wojciszke, 2014) and *Competence* as core social cognition dimensions, enabling analysis of empathy's cognitive-interpersonal aspects (MacDonald, 1992). *Trust* is the basis for believing in others' good intentions, which is necessary for emotional resonance; *Sociability* reflects active affiliation with others, supporting the interpersonal nature of empathy. *Competence* refers to the perceived ability of others to provide help or pose threats, guiding decisions to collaborate or avoid.

EAT posits that emotions are not solely cognitive products but direct bodily responses to environmental stimuli, which aligns with multiple viewpoints. For instance, the Greek philosophy of mind's "qualia" concept holds human mind and cognition roots in sensory experiences. Enactive emotion theories (Hutto, 2012) view emotions as dynamic blends of body, cognition, and environment. Embodied cognition theories dismantle mind-body dualism, asserting cognition arises from body-environment coupling. In communication studies, the concept of "embodied presence" is proposed to describe how people immerse themselves in digital environments (Lindemann and Schünemann, 2020) .

Together, we tentatively infer that empathy may relate to "embodied imaginative resonance", rather than mere psychological projection.

3 Related Work

Here, we focus on works that extract linguistic features from empathetic expressions, alongside empathy prediction and classification tasks.

Linguistic Feature Extraction In early studies, researchers such as Gibson et al. (2015) relied on n-gram and Linguistic Inquiry and Word Count to extract linguistic features. They found that empathic therapists used more abstract perceptual language and reflective phrases such as "it sounds like". Herlin and Visapää (2016) identified via qualitative conversation analysis that a more prominent symmetric reference corresponds to greater emotional sharing, exemplified by the Finnish pronouns "se" (English "it") and "toi" (English "that"). Alam et al. (2016) captured 10k trigram, acoustic and psycholinguistic features from customer service calls, boosting Unweighted Agreement by 31% via majority voting. Similarly, Abdul-Mageed et al. (2017) found 10K unigrams and 50K bigrams optimal for identifying pathogenic empathy. Kann (2017) revealed that empathizers favored self-focused language, while sympathizers preferred other-focused language linked to charitable behaviors. Lee et al. (2024) showed idiom and metaphor features improved RoBERTa-twitter-sentiment performance in figurative empathy recognition.

Empathy Prediction and Classification Tasks Key empathy modeling studies have focused on framework development, model optimization, and task-specific performance improvement: Sharma et al. (2020) proposed the "Epitome" framework (dividing empathy communication into emotional reactions, interpretations, explorations) and developed a RoBERTa-based dual-encoder multitask model (with attention mechanism) for empathy recognition and rationale extraction. Buechel et al. (2018) predicted news-triggered empathy and personal distress, where the Convolutional Neural Network (CNN) achieved Pearson correlations of 0.404 for empathy and 0.444 for distress with human ratings, outperforming Ridge regression and Feed-Forward Network. Guda et al. (2021) proposed the demographic-aware EmpathBERT framework, yielding test set accuracies of 64.73% (male) and 64.56% (female). Dey and Girju (2022) enhanced BERT with FrameNet semantic features, achieving significant improvements in classifying cognitive, affective, and prosocial empathy in premed students' narrative essays. In follow-up work, Dey and Girju (2023) applied Construction and Systemic Functional Grammar theories to doctor-patient prose texts. Their findings showed that the Body Part + Process construction (e.g., "Her eyes welled up"), an important linguistic indicator, improved the BERT model's F_1 score by 7%.

To our knowledge, existing studies cover surface-to-semantic features and integrate text-based and cross-modal data, yet overlook empathy's cognitive-social essence and social media contexts. Methodologically, they prioritize prediction and dialogue generation over classification, while neural networks and LLM-oriented approaches, though widely adopted, face trade-offs between computational cost and the interpretability of linguistic communication mechanisms.

Therefore, our key contributions lie in expanding comprehensive empathy feature design for classification tasks and identifying empathy's underlying linguistic patterns.

4 Dataset

We collected 8,000 tweets using the retrieval hashtag **#California wildfires** (January 1–March 26, 2025), filtered noise and short posts (<2 words) to retain 6,246 samples, and pre-annotated them via DeepSeek-R1 (configured with a temperature of 0.1 and max_tokens of 1) using empathy's three component rules (emotion, cognition, behavior) (Hoffman, 1984) with labels: 0 (irrelevant), 1 (no empathy), 2 (empathy).

To verify the agreement between LLM pre-annotations and human annotations, we used Cohen's Kappa coefficient (via scikit-learn in Python) on 189 random samples, yielding Kappa ≈ 0.68. Both the LLM and the manual annotator followed the same annotation scheme (Appendix A). Taking human annotations as the gold standard, we further evaluated LLM's classification performance and report precision/recall/F_1, with 0.70 overall accuracy, 0.91 precision for empathy (Category 2), and 0.75 recall for no empathy (Category 1) (Appendix 7). Subsequently, the trained researcher systematically reviewed and corrected all LLM-generated labels. Dataset distribution (Table 1) shows relative balance across empathy categories.

5 Lexical Analysis

We analyzed lexical differences between empathetic and non-empathetic texts, laying groundwork for precise feature design in later stages.

Inspired by the distributional consistency framework for distinguishing core lexicons Huang et al. (2005), as well as the application of normalized deviation of proportions (DP_{norm}) in fake news detection Wan et al. (2022), this study also employs DP_{norm} to quantify lexical usage differences, defined as:

$$DP_{\text{norm}} = \frac{DP}{1 - \min_i(s_i)}$$

DP is calculated as:

$$DP = \left(\sum_{i=1}^{n} |s_i - v_i| \right) /2$$

Here, s_i denotes the relative size of texts (proportion of text length in subset i), v_i the observed relative frequency of a lemma in subset i. The higher value shows stronger association with the subset.

We retained 113 discriminative lemmas with a threshold of $DP_{norm} \geq 0.7$, and present word clouds of selected lemmas: empathetic in Figure 1 and non-empathetic in Figure 2. Complete lists of lemmas are provided in Appendices 6 and 7.

Figure 1: Top 30 Empathetic Lemmas (sorted by DP_{norm} descending)

Figure 2: Top 28 Non-Empathetic Lemmas (sorted by DP_{norm} descending)

Key preliminary findings are summarized:

Empathy Targets: Empathetic texts consistently mention vulnerable groups (e.g., "community", "child") and blur in-group/out-group boundaries. Non-empathetic texts emphasize "power" and "authorities": their transactional, emotionally disengaged language aligns with Lewin (2013)'s approach-avoidance theory (suppressed "approach-connection" motives).

Empathy Triggers: Empathetic lexicons include solidarity terms ("pray", "give", "donate"), social process words, and moral-altruistic vocabulary, often tied to blessing and charity. Non-empathetic texts cluster around contentious topics (e.g., politics), which highlight in-group/out-group divisions (Vanman, 2016) and likely dampen empathy toward out-groups.

Despite lexical meaning being context-dependent, these patterns spark semantic feature design (e.g., sociality) in subsequent analyses.

6 Feature Design

From text data, we extracted three feature types: Cognitive, Perceptual, and Syntactic Features.

6.1 Cognitive and Perceptual Features

Sociability and Trust As introduced in SCM (*Warmth* (including *Sociability* and *Trust*) and competence are the two core dimensions of social cognition, which we rely on to evaluate individuals and groups. Here, we hypothesize that lexical use tied to high sociability and trust positively correlates with empathetic expression.

Trust and *Sociability* scores were computed by aggregating word-level scores from Words of Warmth norms (Mohammad, 2025), which quantify the inherent social-cognitive attributes of over 26,000 English words. (e.g., "prayer" : *Sociability score* [S] = 0.952, *Trust score* [T] = 0.848, competence [C] = 0.208; "resign" : S = -0.333, T = 0.273,

Table 1: Dataset distribution

Characteristics	Empathy	No Empathy	Irrelevant
Number of Samples	2,113 (33.83%)	2,995 (47.95%)	1,138 (18.22%)
Total Tokens	54,997 (40.15%)	59,204 (43.21%)	22,819 (16.64%)
Total Sentences	3,949 (33.17%)	5,639 (47.37%)	2,309 (19.46%)
Avg. Tokens/Sample	26.03	19.77	20.05
Avg. Sentences/Sample	1.87	1.88	2.03

Note: Total samples = 6,246; Total tokens = 137,020; Total sentences = 11,897

Text	Trust	Sociability
God bless.	0.870	0.955
God help!	0.741	0.939
Stupid,Ridiculous,Dangerous,Wasteful.	**-0.418**	**-0.678**
No conspiracy theorists without conspiracy terrorists.	**-0.455**	0.000

Table 2: Sentence-level score examples: Trust and Sociability dimensions

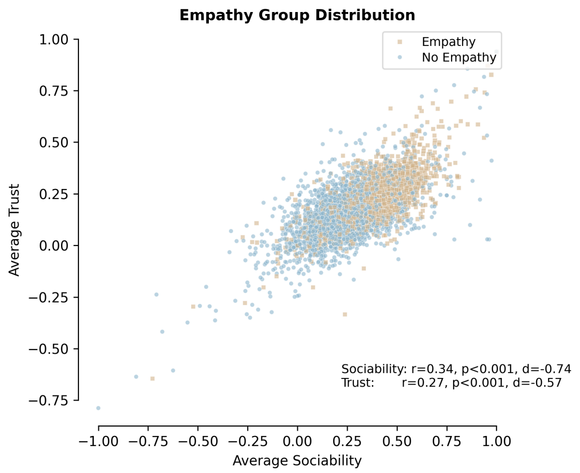

Figure 3: Dimensional distribution between S and T

C = -0.454). Sentence-level examples appear in Table 2. Figure 3 is the sentence-level distribution: *Sociability* (horizontal axis) exhibits a larger effect size (Cohen's d = 0.74) than *Trust* (vertical axis, Cohen's d = 0.57). This upward aggregation process is detailed in Appendix Figure 8.

Embodied Strength It reflects the strength of perceived embodied presence, defined as how strongly one feels physically immersed in others' environment. Grounded in EAT, we hypothesize that more specific sensory details in text will strengthen this embodied presence, thereby eliciting higher empathy.

Embodied scores were computed using Lancaster Sensorimotor Norms (Lynott et al., 2020), which provide sensory ratings for over 40,000 English words across six dimensions (Interoceptive, Auditory, Gustatory, Olfactory, Visual, and Haptic). The norms were used to compute embodied scores via a weighted formula, where coefficients (coef) determined via linear regression. Results ($t = 5.36$, $p < 0.005$, Cohen's $d = 0.16$) indicate that empathic individuals express solidarity by constructing vivid situational contexts that foster a sense of co-presence, as shown by example phrases (Figure 4, Table 3).

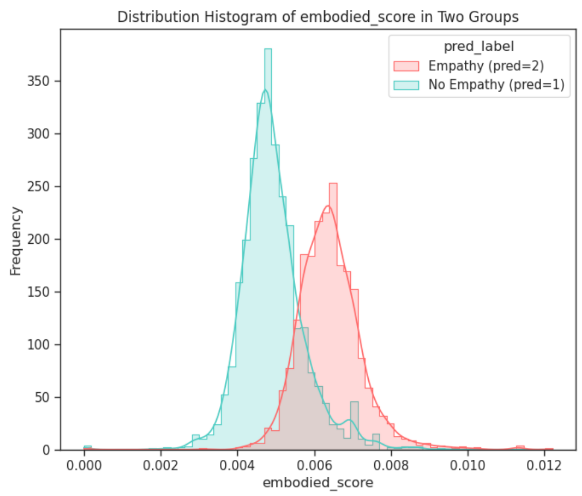

Figure 4: Distribution of embodied score in two groups

Table 3: Sentence-level embodied scores examples

High Embodied score (Top 3)
1. Indigenous man art pieces survived California fires.
2. News accidentally shows human skeleton.
3. I got a briefing at the Command Post and saw first-hand the devastation on Sunset Boulevard and Pacific Coast Highway. Let's come together to help the thousands of Angelenos who lost their homes.
Low Embodied score (Bottom 3)
1. What The Future For Los Angeles?
2. Forget the donate to the Dems.
3. What started the California wildfires?

6.2 Syntactic Features

Parts of Speech Using the Penn Treebank POS tagger, 36 POS tag ratios were generated. The most impactful feature, proper noun singular (NNP), appears more frequently in non-empathetic texts (pred = 1). These include specific references such as names, places, and institutions (e.g., ARMAGEDDON, MAGA, NYFD), many of which are cultural symbols whose mention may trigger audience identification or controversy. By contrast, the empathy group (pred 2) uses more deindividuated language and vague references such as “those” (referring to victims) or “what they went through” (Figure 5).

This pattern aligns with Markedness theory (Francis, 2007), which distinguishes two types of linguistic choices: “marked” (deviant and attention-requiring) and “unmarked” (default and conventional). In empathetic communication, the unmarked strategy prioritizes de-individualization and shared emotional resonance, reducing individual specificity to broaden its reach.

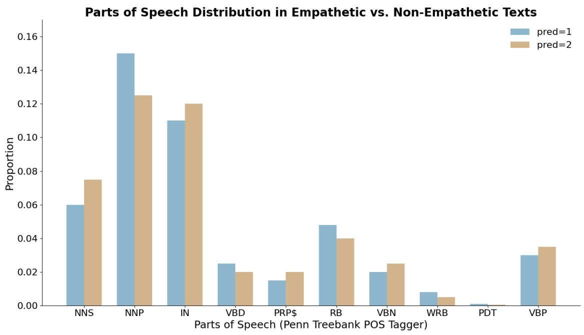

Figure 5: Distribution of parts of speech between empathetic and non-empathetic groups

Sentence Structures We analyzed 10 key sentence types using Stanford CoreNLP. Three showed significant group differences (p < 0.01), with imperatives most notable: the empathetic group used more imperatives (e.g., “Please help them”) to emphasize action in emergencies, while the non-empathetic group preferred interrogatives (e.g., “Do you trust the foundation?”) to focus on questioning. (Figure 6)

7 Predictive Power

Logistic Regression This experiment examined the correlation between proposed features (independent variables) and empathy levels (dependent variable) to identify the most predictive linguistic markers. Model performance was evaluated using average coefficients, p-values, and Cohen’s d. Meanwhile, 10-fold cross-validation yielded an average accuracy of 0.68.

Results (Table 4) highlight avg_sociability as the most informative feature, followed by imperative

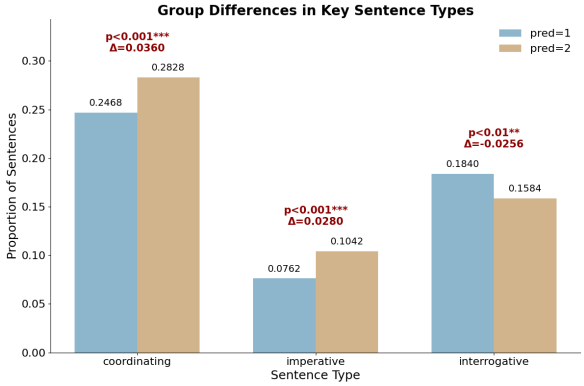

Figure 6: Distribution of sentence structures (Top 3 types) between empathetic and non-empathetic groups

proportion (imperative_prop), NNP, and Embodied score. Notably, the embodied score offers unique supplementary value as it illuminates empathy’s linguistic patterns through sensory experience. Moreover, negative coefficients for avg_competence and interrogative_prop support prior findings: empathizers focus on vulnerable targets rather than ability evaluations. Non-empathetic individuals tend to use rhetorical questions, intentionally or unintentionally creating “difference” rather than pursuing emotional alignment.

Table 4: Variables importance ranking (10-Fold Cross-Validation)

Variable	Avg. Coef	Coef Std	Cohen’s d	Sig.
avg_sociability	0.386	0.020	0.390	***
imperative_prop	0.253	0.058	0.128	***
NNP	-0.176	0.013	-0.168	***
Embodied	0.172	0.013	0.201	***
avg_competence	-0.120	0.010	0.067	*
avg_trust	0.117	0.017	0.309	***
interrogative_prop	-0.116	0.007	-0.084	**
politeness_score	0.104	0.008	0.183	***
coordinating_prop	0.024	0.015	0.101	**

Sig.: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

8 Machine Learning Models

Building on prior predictive power analysis, we further validated these features through classification tasks. Three models—logistic regression (LR), support vector machine (SVM), and random forest (RF), were used to test feature generalization. The top 3 key features (400D TF-IDF baseline supplemented by handcrafted features) were input to train the classifiers. Evaluation combined 10-fold cross-validation with an independent test set, with F_1 and AUC as core metrics.

Results (Table 5) show that Sociability, as the most impactful feature, improves LR's F_1 by 4.68% over the baseline and consistently enhances F_1 and AUC across models. Combining all features (the top 3 features) yields the best performance, with SVM achieving the highest F_1 (0.689) and LR leading in AUC (0.718), verifying the synergistic and complementary effects of multi-dimensional features. However, there are differences in model adaptability: RF naturally adapts to heterogeneous handcrafted features, LR relies on feature weight optimization, and SVM is sensitive to feature combinations but has limited utilization of single features. In conclusion, subtle performance optimizations still matter in complex tasks such as empathy classification.

Table 5: Model Performance with TOP 3 Features

Model	Features	F_1 (Mean)	F_1 (Std)	AUC (Mean)	AUC (Std)
LR	Baseline	0.624	0.021	0.676	0.024
	S	0.671	0.022	0.712	0.023
	I	0.636	0.024	0.688	0.027
	NNP	0.625	0.021	0.676	0.024
	All	**0.683**	0.016	**0.718**	0.020
SVM	Baseline	0.614	0.016	0.648	0.027
	S	0.672	0.025	0.710	0.024
	I	0.634	0.026	0.672	0.027
	NNP	0.622	0.016	0.648	0.025
	All	0.689	0.020	0.722	0.024
RF	Baseline	0.597	0.017	0.627	0.023
	S	0.643	0.011	0.654	0.019
	I	0.629	0.016	0.633	0.017
	NNP	0.602	0.010	0.629	0.021
	All	0.673	0.027	0.712	0.030

S: avg_sociability; I: imperative_prop.

9 Conclusion

We adopted a comprehensive computational method to uncover empathy's communication patterns at the group level. Integrating SCM and EAT, we identified signals distinguishing empathetic vs. non-empathetic expression, analyzed usage differences, and validated their effectiveness via supervised learning in the empathy classification task. We summarized two new findings:

- **Empathy and sociability**: Sociability emerges as the strongest predictor of empathy (supported by DP-norm lists and model results). This highlights a key trait of empathetic language: stronger affiliation intentions drive richer empathetic communication.

- **Empathy and perceived embodied presence**: Greater sensory perception intensity correlates with stronger empathetic resonance. Theoretically, this extends the theory of communication's "embodied presence" to the context of social media disasters. Specifically, the empathetic group prefers concrete, vivid sensory details (e.g., "stand with you") to build a sense of co-presence.

These findings enrich empathy's multiple representations and highlight its interplay with cognition, embodiment, and interpersonal dimensions. We hope to pave the way for follow-up research on generalizing to near-synonymous affective expressions (e.g., "mercy," "care," "sympathy") or other implicit ones.

Limitations

First, potential annotation subjectivity exists despite extensive bias-mitigation measures. Second, we focus on textual features. Future work will expand contexts and integrate multimodal data to enhance real-world empathy modeling.

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References

Muhammad Abdul-Mageed, Anneke Buffone, Hao Peng, Salvatore Giorgi, Johannes Eichstaedt, and Lyle Ungar. 2017. Recognizing Pathogenic Empathy in social media. In *Proceedings of the 11th International AAAI Conference on Web and Social Media*, pages 448–451, Montreal, Canada. AAAI Press.

Andrea E. Abele and Bogdan Wojciszke. 2014. Communal and agentic content in social cognition: A dual perspective model. *Advances in Experimental Social Psychology*, pages 198–255.

Firoj Alam, Morena Danieli, and Giuseppe Riccardi. 2016. Can we detect speakers' empathy?: A real-life case study. *2016 7th IEEE International Conference on Cognitive Infocommunications (CogInfoCom)*, pages 000059–000064.

Sven Buechel, Anneke Buffone, Barry Slaff, Lyle Ungar, and João Sedoc. 2018. Modeling empathy and distress in reaction to news stories. In *Proceedings of the 2018 Conference on EMNLP*, pages 4758–4765, Brussels, Belgium. ACL.

Amy Coplan and Peter Goldie. 2011. *Empathy: Philosophical and Psychological Perspectives*. Oxford University Press.

P. Dey and R. Girju. 2022. Enriching deep learning with frame semantics for empathy classification in medical narrative essays. In *Proceedings of the 13th International Workshop on Health Text Mining and Information Analysis (LOUHI)*, pages 207–217, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.

Priyanka Dey and Roxana Girju. 2023. Investigating stylistic profiles for the task of empathy classification in medical narrative essays. In *Proceedings of the First International Workshop on Construction Grammars and NLP (CxGs+NLP, GURT/SyntaxFest 2023)*, pages 63–74, Washington, D.C. Association for Computational Linguistics.

Susan T. Fiske, Amy J. C. Cuddy, Peter Glick, and Jun Xu. 2002. A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of personality and social psychology*, 82(6):878–902.

Norbert Francis. 2007. Carol myers-scotton: Multiple voices: An introduction to bilingualism. *Applied Linguistics*, 28(1):155–158.

James Gibson, Nikos Malandrakis, Francisco Romero, David C. Atkins, and Shrikanth S. Narayanan. 2015. Predicting therapist empathy in motivational interviews using language features inspired by psycholinguistic norms. In *Interspeech*.

Bhanu Prakash Reddy Guda, Aparna Garimella, and Niyati Chhaya. 2021. Empathbert: A bert-based framework for demographic-aware empathy prediction. *CoRR*, abs/2102.00272.

Ilona Herlin and Laura Visapää. 2016. Dimensions of empathy in relation to language. *Nordic Journal of Linguistics*, 39(2):135–157.

M. L. Hoffman. 1984. Interaction of affect and cognition in empathy. *Emotion, Cognition, and Behavior*, pages 103–131.

Chu-Ren Huang, Huarui Zhang, and Shiwen Yu. 2005. *On Predicting and Verifying a Basic Lexicon: Proposals inspired by Distributional Consistency*, pages 57–69.

Daniel Hutto. 2012. Truly enactive emotion. *Emotion Review*, 4:176–181.

Trevor Kann. 2017. *Measuring Linguistic Empathy: An Experimental Approach to Connecting Linguistic and Social Psychological Notions of Empathy*. Ph.D. thesis, University of California, Los Angeles.

Gyeongeun Lee, Christina Wong, Meghan Guo, and Natalie Parde. 2024. Pouring your heart out: Investigating the role of figurative language in online expressions of empathy. In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 519–529, Bangkok, Thailand. ACL.

K. Lewin. 2013. *A Dynamic Theory of Personality - Selected Papers*. Read Books Limited.

Gesa Lindemann and David Schünemann. 2020. Presence in digital spaces. a phenomenological concept of presence in mediatized communication. *Human Studies*, 43(4):627–651.

Dermot Lynott, Louise Connell, Marc Brysbaert, James Brand, and James Carney. 2020. The lancaster sensorimotor norms: Multidimensional measures of perceptual and action strength for 40,000 english words. *Behavior Research Methods*, 52:1271–1291.

Kevin MacDonald. 1992. Warmth as a developmental construct: An evolutionary analysis. *Child Development*, 63:753–773.

Saif M. Mohammad. 2025. Words of warmth: Trust and sociability norms for over 26k English words. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 18830–18850, Vienna, Austria. ACL.

Becky Lynn Omdahl. 1995. *Cognitive Appraisal, Emotion, and Empathy*. Lawrence Erlbaum.

Rosalind W. Picard. 1997. Affective computing.

J.J. Prinz. 2004. *Gut Reactions: A Perceptual Theory of Emotion*. Philosophy of Mind. Oxford University Press.

Ashish Sharma, Adam Miner, David Atkins, and Tim Althoff. 2020. A computational approach to understanding empathy expressed in text-based mental health support. In *Proceedings of the 2020 Conference on EMNLP*, pages 5263–5276, Online. ACL.

E. J. Vanman. 2016. The role of empathy in intergroup relations. *Current Opinion in Psychology*, 11:59–63.

Clara M. Wan, Qi Su, Rong Xiang, and Chu-Ren Huang. 2022. Data-driven analytics of covid-19 'infodemic'. *International Journal of Data Science and Analytics*, 15.

A Appendix

A Annotation

Prompt Instructions Classify tweets regarding the 2024-2025 California wildfires into three categories based on empathy expression:

2 (empathy): Tweets show empathy toward the wildfire disaster. Trigger if any of these apply:

- Affective Empathy: Expressions of sadness, sympathy, mourning, comfort, worry, or support (e.g., "Praying for families affected by California wildfires").
- Cognitive Empathy: Rational understanding of impacts (e.g., policy failures, environmental damage) or solution-oriented analysis (e.g., "Better forest management could reduce wildfire risks").
- Behavioral Intent: Calls to action (donations, volunteer work, advocacy) (e.g., "Donate to help wildfire victims").

1 (no empathy): Tweets lack empathy. Trigger:

- Detached/Sarcastic: Cynical, mocking, or critical tones (e.g., "California wildfires? Just nature's population control").
- Trivializing: Entertainment-focused or flippant framing (e.g., "Another year of barbecued California #wildfireseason").
- Indirect/Uncaring: Disaster-related context but no concern (e.g., "CaliforniaWildfires? Idiots in power caused this").

0 (irrelevant): Tweets are objective news updates unrelated to empathy)

Classification Criteria Leverage semantic content, emotional tone, disaster context to determine

- 2 (empathy): Emotional concern, rational understanding of impacts, or proactive support.
- 1 (no empathy): Cynicism, trivialization, or uncaring tones in a disaster context.
- 0 (irrelevant): Purely factual updates (no empathy/antipathy).

Examples align with these rules (e.g., "Praying for victims" = 2; "Wildfires? Just nature's way" = 1; "Fire size: 5,389 acres" = 0).

Experimental Metrics and Results

	precision	recall	f1-score	support
0	0.23	0.50	0.31	18
1	0.78	0.75	0.76	99
2	0.91	0.68	0.78	72
accuracy			0.70	189
macro avg	0.64	0.64	0.62	189
eighted avg	0.78	0.70	0.73	189

Figure 7: LLM Classification Performance

B Supplementary Materials

B.1 Complete Lexical Lists for Empathy and Non-Empathy

see Table 6 and Table 7.

Rank	Lemma	DP_norm	Rank	Lemma	DP_norm	Rank	Lemma	DP_norm
1	prayer	0.99	30	displaced	0.88	59	thanks	0.79
2	pet	0.98	31	community	0.88	60	neighbor	0.79
3	heart	0.98	32	family	0.87	61	critical	0.79
4	drive	0.98	33	thank	0.87	62	learn	0.79
5	shelter	0.98	34	helping	0.87	63	everyone	0.79
6	foundation	0.98	35	recover	0.87	64	member	0.79
7	impacted	0.96	36	hero	0.86	65	join	0.79
8	donate	0.96	37	donation	0.86	66	care	0.78
9	organization	0.95	38	relief	0.86	67	impact	0.78
10	animal	0.95	39	safe	0.86	68	update	0.78
11	volunteer	0.95	40	charity	0.86	69	devastation	0.77
12	affected	0.94	41	jan	0.85	70	lost	0.77
13	responder	0.94	42	open	0.85	71	benefit	0.76
14	difference	0.93	43	sending	0.85	72	center	0.76
15	rescue	0.93	44	survivor	0.84	73	offer	0.76
16	supporting	0.93	45	stay	0.84	74	recent	0.75
17	food	0.92	46	link	0.84	75	first	0.75
18	pray	0.92	47	devastating	0.84	76	important	0.75
19	together	0.92	48	child	0.83	77	across	0.75
20	providing	0.91	49	school	0.83	78	folk	0.74
21	resource	0.91	50	small	0.82	79	including	0.73
22	raise	0.90	51	help	0.81	80	donated	0.72
23	effort	0.90	52	recovery	0.81	81	stand	0.72
24	assistance	0.90	53	donating	0.81	82	supply	0.71
25	amazing	0.89	54	hope	0.80	83	service	0.71
26	altadena	0.89	55	please	0.80	84	firefighter	0.71
27	support	0.89	56	love	0.80	85	information	0.70
28	team	0.88	57	share	0.80			
29	working	0.88	58	friend	0.80			

Table 6: Distinct Lemmas for Empathy (85 words)

Rank	Lemma	DP_norm	Rank	Lemma	DP_norm	Rank	Lemma	DP_norm
1	resign	1.00	11	money	0.94	21	cagovernor	0.81
2	vote	1.00	12	president	0.93	22	chief	0.80
3	trump	0.98	13	potus	0.91	23	cut	0.79
4	rickcaruso	0.96	14	mayor	0.89	24	tax	0.74
5	bass	0.95	15	elonmusk	0.88	25	government	0.73
6	karenbass	0.95	16	gavinnewsom	0.88	26	something	0.73
7	arson	0.95	17	knew	0.87	27	real	0.73
8	right	0.94	18	newsom	0.86	28	official	0.71
9	gavin	0.94	19	tell	0.85			
10	democrat	0.94	20	policy	0.85			

Table 7: Distinct lemmas for non-empathy (28 words)

B.2 Calculation of Sentence-Level Trust and Sociability Scores

Combined lexicon-based exact matching with GloVe semantic retrieval (cosine threshold = 0.5) for unmatched tokens. (Figure 8).

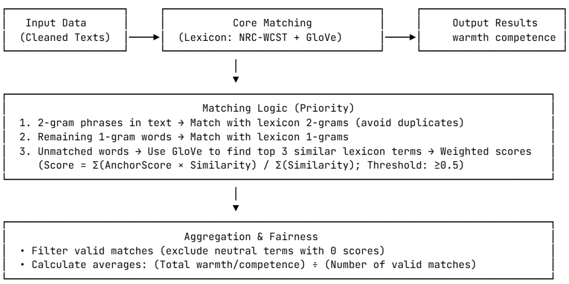

Figure 8: A flowchart showing the process of calculating sentence-level trust and sociability scores