REPETITION, BELIEF, AND TRUTH IN FAKE NEWS: REVEALED BY PHYSIOLOGICAL SIGNALS

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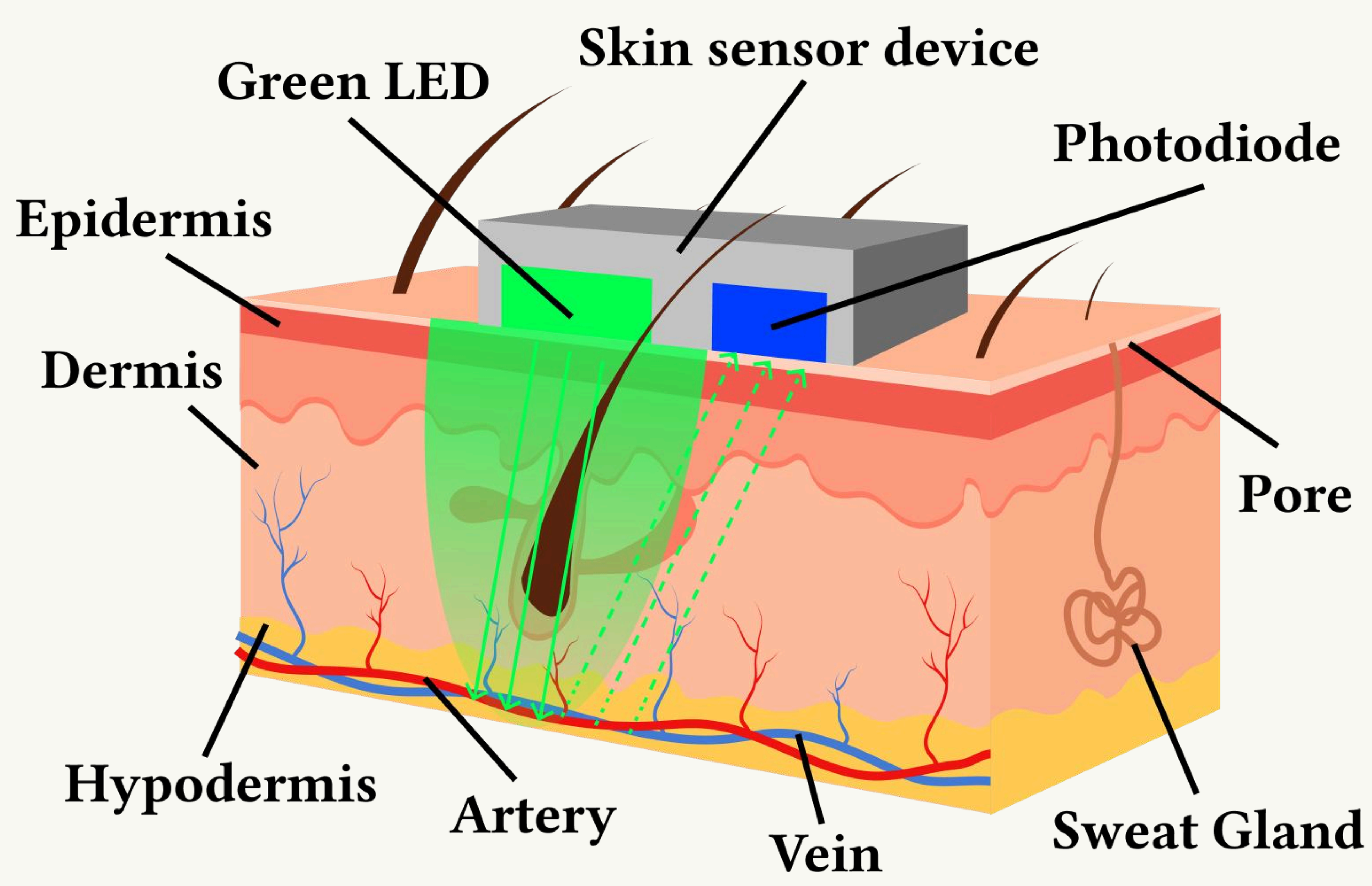
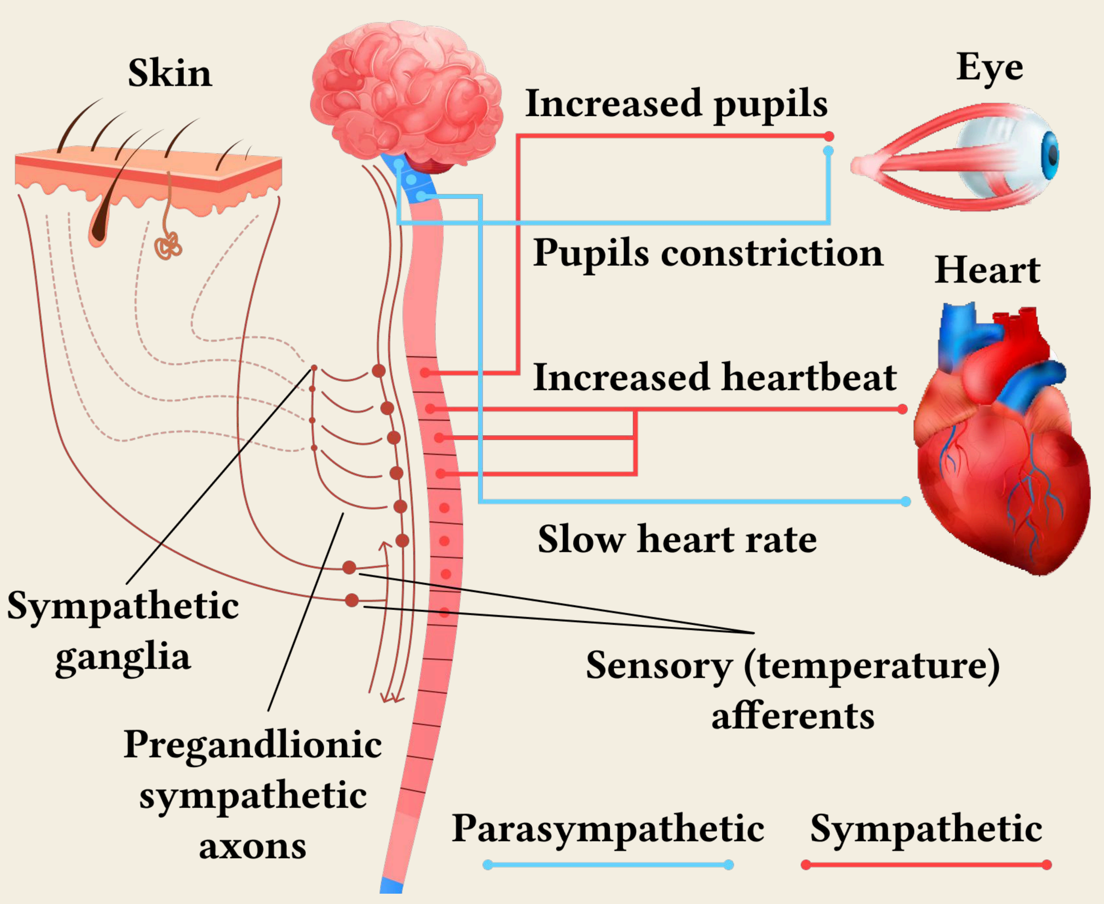


MOTIVATION & KEY IDEA I

Why this matters

Misinformation spreads rapidly online, threatening public trust, health, and democracy. While most computational methods focus on content (e.g., text analysis), few consider how humans emotionally and physiologically react to false or repeated information.



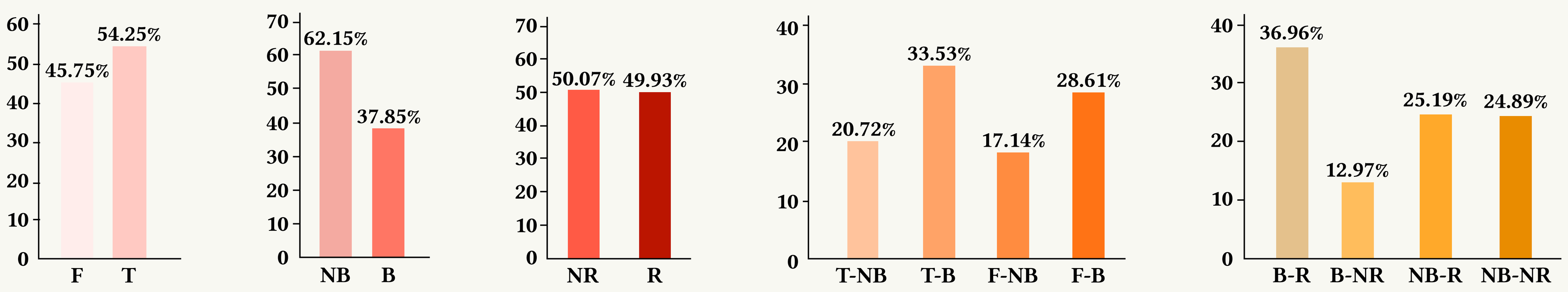
Our approach

We investigate whether low-cost physiological signals, like EDA and PPG, can reveal how people respond to misinformation in terms of belief, perceived truth, and repetition.

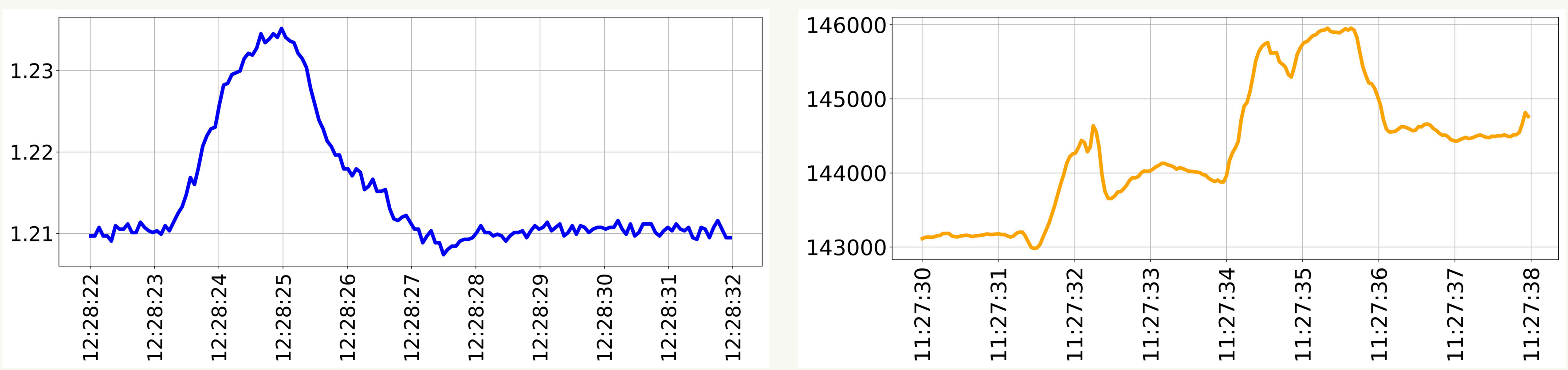
Why it's different

- Goes beyond intentional deception: focuses on everyday digital encounters
- Captures subtle, unconscious reactions during truth evaluation
- Aims to integrate human responses into future misinformation detection systems

CONTRIBUTIONS III



1. Introduce **a novel dataset** combining EDA & PPG with human belief, truth, and repetition labels;
2. **Evaluate 5 classification tasks**: Belief (B/NB), Repetition (R/NR), Truth (T/F), Joint Belief–Repetition, Joint Belief–Truth;
3. **Compare 3 models** (KNN, LightGBM, CNN): KNN consistently performs best, EDA outperforms PPG, and joint tasks remain most challenging;
4. Our findings show that **physiological signals encode subtle markers of misinformation susceptibilit**y, enabling future adaptive and user-aware detection systems.



Samples of trials in the dataset, with EDA data in the left and PPG in the right

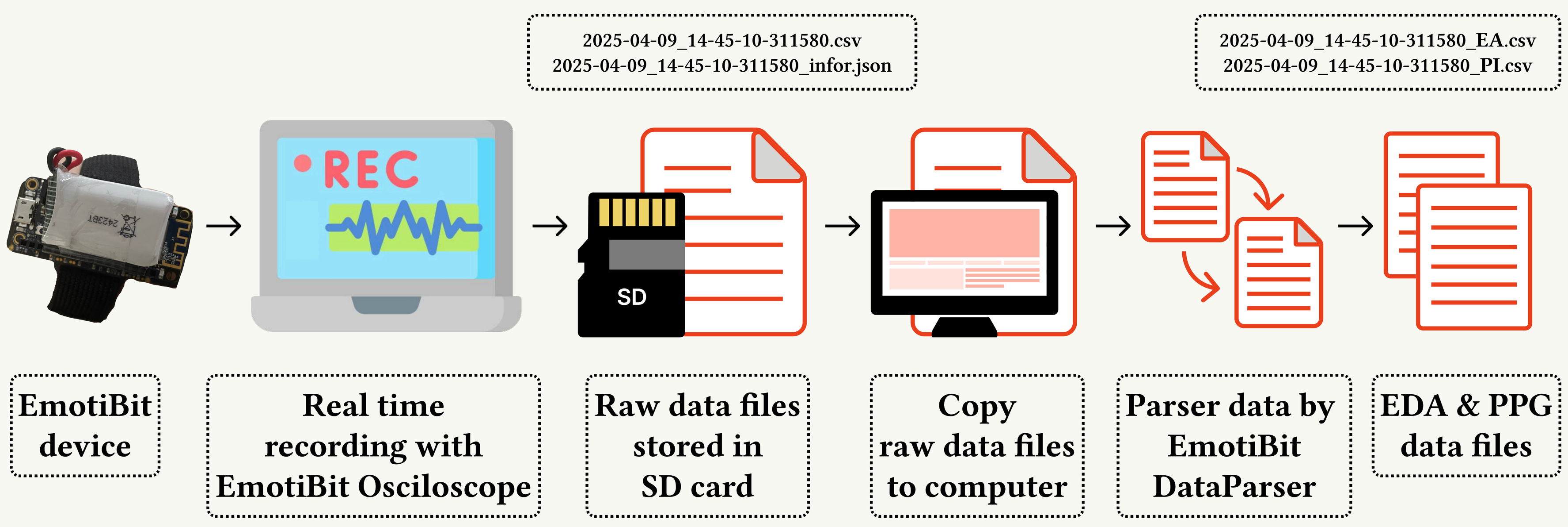
METHOD II

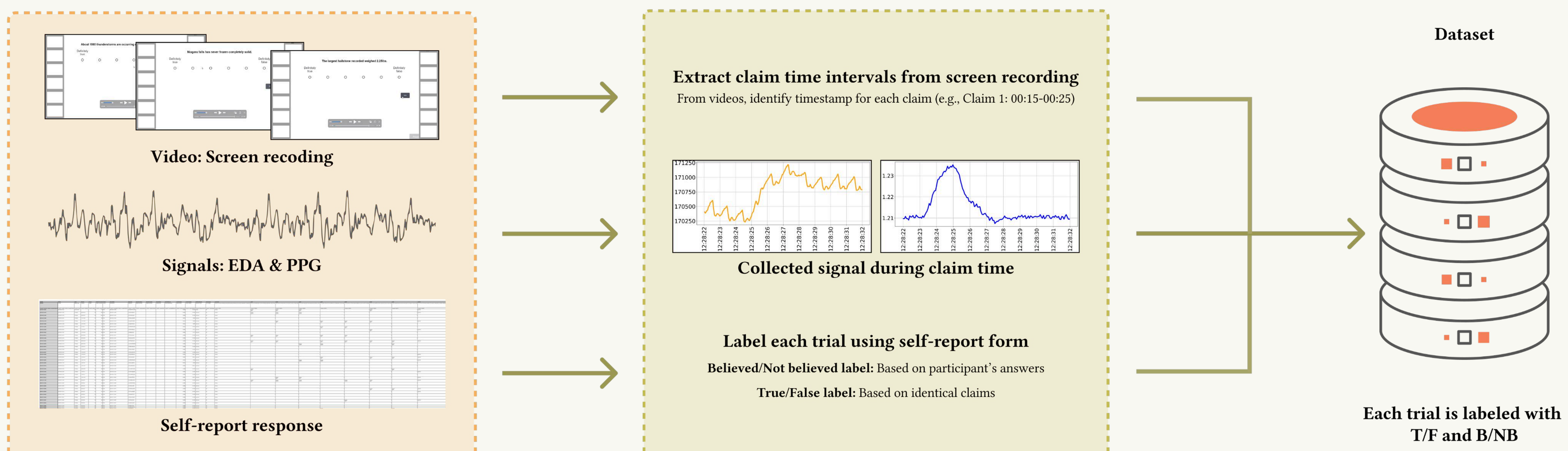
Experiment Design

We conducted a controlled lab study with 28 participants, each evaluating 24 factual climate-related claims while wearing EmotiBit sensors that recorded two physiological signals:

- **EDA**: linked to emotional arousal and attention
- **PPG**: linked to cognitive load and cardiovascular regulation

Participants first viewed a subset of claims (encoding), completed a filler task (distraction), then judged truthfulness (evaluation). Signals were recorded during the evaluation phase.





Data Processing & Features

Each trial corresponds to a claim and the signals collected during the time the participant interacts with that claim was labeled with:

- **Objective truth** (True / False)
- **User belief** (Believe / Not Believe)
- **Repetition** (Repeated / Not Repeated)

Signals were segmented per trial, cleaned, and normalized. We extracted features across time, frequency, and complexity domains. Top 7–15 features were selected via KNN-based ranking

Classification tasks

Five classification tasks reflecting different cognitive dimensions of misinformation:

1. **Repetition:** Has the claim been shown before? (R / NR)
2. **Belief:** Does the user believe the claim? (B / NB)
3. **Veracity:** Is the claim objectively true? (T / F)
4. **Joint Belief-Veracity:** Four-class (T-B, T-NB, F-B, F-NB)
5. **Joint Belief-Repetition:** Four-class (B-R, B-NR, NB-R, NB-NR)

RESULTS IV

Our results demonstrate that **physiological signals, especially EDA, can reliably reflect users' belief, repetition, and truth judgments**. Across all five classification tasks, KNN consistently outperformed LightGBM and CNN, particularly on EDA data, highlighting the robustness of instance-based models in low-resource and noisy contexts.

While binary tasks such as belief and repetition yielded strong F1 scores (with highest as 64%), performance dropped significantly for the joint belief-veracity task and joint repetition-truth, suggesting the difficulty of decoding compound cognitive states from unimodal biosignals. These findings emphasize both the potential and the limits of physiological computing in understanding human responses to misinformation.

Model	Metrics	Repetition classification		Belief classification		Veracity classification		Joint Belief-Repetition		Joint Belief-Veracity	
		EDA	PPG	EDA	PPG	EDA	PPG	EDA	PPG	EDA	PPG
KNN	Accuracy	63.64	**65.97**	**67.83**	59.72	**65.73**	**61.11**	**45.45**	37.50	**37.06**	31.94
	Precision	64.15	66.05	77.12	60.31	65.66	61.11	33.16	24.69	42.50	29.97
	Recall	63.57	65.97	63.28	54.60	64.62	61.19	37.54	29.85	34.75	30.57
	F1 Score	63.20	65.92	60.77	49.58	64.57	61.04	32.84	25.09	34.00	29.58
LightGBM	Accuracy	**67.13**	63.19	59.72	61.90	59.72	59.03	42.36	**38.89**	33.33	32.64
	Precision	67.42	63.33	63.49	54.18	64.03	58.52	40.82	27.56	27.96	30.82
	Recall	67.18	63.19	61.88	52.76	56.76	57.98	34.29	31.33	28.75	29.25
	F1 Score	67.01	63.10	58.99	51.32	51.95	57.75	30.83	27.55	24.88	27.80
CNN	Accuracy	57.46	54.07	63.34	**62.22**	54.34	54.07	36.57	36.30	36.57	**35.56**
	Precision	67.74	58.59	59.81	56.39	52.46	52.24	9.21	9.14	38.02	31.44
	Recall	57.36	54.34	56.87	51.16	50.81	50.73	24.50	24.50	28.10	28.45
	F1 Score	42.39	47.67	56.06	43.39	42.56	42.17	13.39	13.32	18.64	23.56

**This work contains papers under review in ICMI 2025 and CSCW 2026.*