A fuzzy logic approach for mapping associations between color and emotion dimensions

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INTRODUCTION AND MOTIVATION

Color–concept associations aid visualization, but color-emotion associations are abstract, vague and vary between people.

Can a data-trained fuzzy system predict an emotion's color from its valence, arousal and dominance (VAD)?

DATASET

78	22	3
participants	emojis	tasks

- **Emoji–Color:** pick the color (L*a*b*) you associate with the emoji.
- **Label–Color:** name the emoji, then pick a color for that label.
- **Emotion rating:** rate valence, arousal and dominance (VAD).

FUZZY LOGIC MODEL

VAD (3 inputs) → **TS fuzzy system** FMID toolkit → **L*a*b*** (3 outputs)

One model for emojis, one for labels. All tested settings gave similar MSE, so we chose the simplest: **3 rules.**

Reading the rules

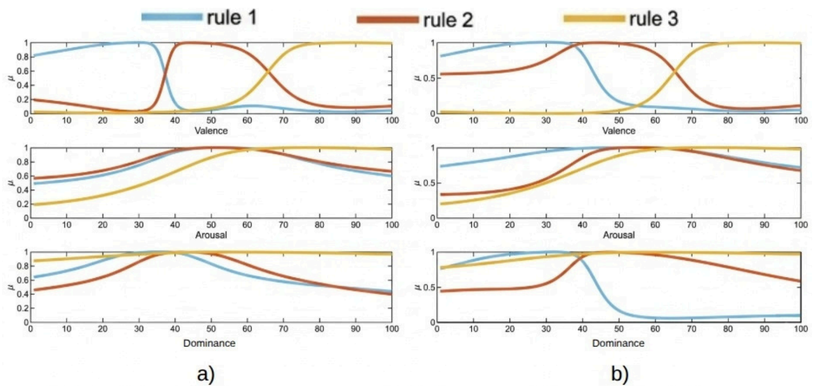


Fig. 1. Membership functions, emojis (a) and labels (b).

Each rule blends linear L*a*b* consequents, weighted by how strongly the VAD input fires it. Together they partition the emotion space:

Table 1. Partition of the VAD space learned by the antecedents.

Color	Valence	Arousal	Dominance
Red	low–med	high	medium
Blue	low	low–med	low
Yellow	med–high	high	med-high

RESULTS

Predicted colors are smoother and less saturated than participants' choices: the fuzzy rules capture the global trends of the color–emotion relationship rather than individual responses.

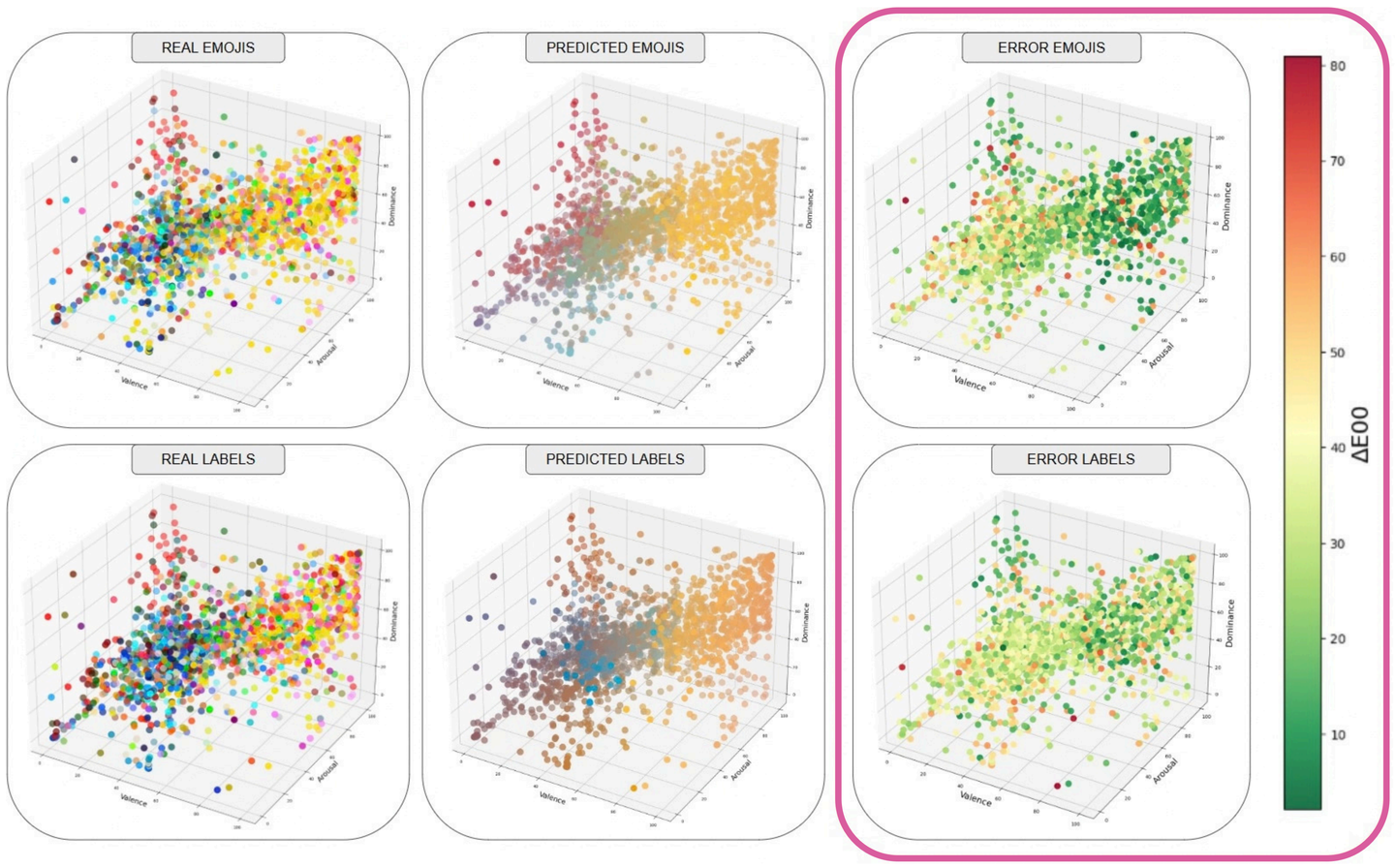


Fig. 2. Emojis (top) and labels (bottom): participants' colors, predictions and ΔE00 error. Predictions are smooth where raw data are scattered; errors are lowest at high VAD and highest in the ambiguous center.

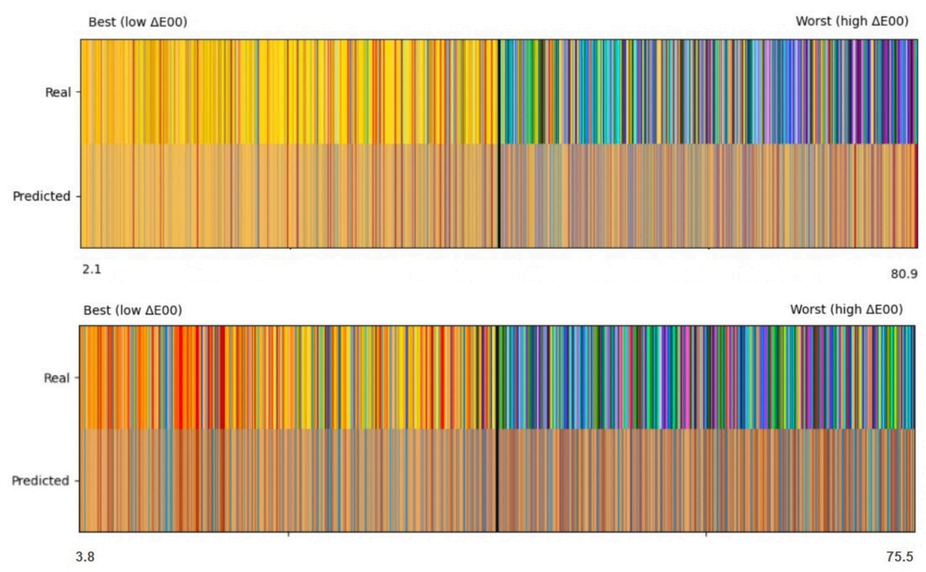
Prediction error

Errors were measured with ΔE00. Mean errors are high (≈30 for emojis, ≈33 for labels) because the rules capture general trends, not individual responses. Train and test errors are almost identical, so the models do not overfit.

Table 2. Mean ± std ΔE_{00} of train and test.

ΔE_{00}	n	Emojis	Labels
Train	1225	29.93 ± 15.48	33.06 ± 11.96
Test	523	30.75 ± 15.74	32.78 ± 12.26

The colors with the lowest errors are ***yellow*** and ***red*** and those with the highest errors are ***blue*** and ***green***. This may reflect a bias in emoji-related tasks, as emojis are often associated with the color yellow.



The predicted colors are less saturated than the original colors and tend to be more yellowish. This leads to lower errors for yellowish-reddish colors and higher errors for blue and green.

In the VAD space, some colors are clustered in delimited regions whereas others are spread over a broader region due to their ambiguous relation to emotion.

Fig. 3. Emojis (top) and labels (bottom): real vs. predicted ordered from left (lowest error) to right (highest error).

CONCLUSIONS

- Fuzzy logic gives an **interpretable** model of uncertain color–emotion links.

  It captures **global trends**; ΔE_{00} ≈ 30–33 mainly reflects interpersonal variability.

- Vivid **yellows and reds** are predicted best.
  Blues and greens are predicted worst, shifted to yellow (emojis) or pink (labels) — cool tones span broad, ambiguous VAD regions.

- Next steps: context, more dimensions, adaptive and probabilistic fuzzy models.

Key references. L. A. Zadeh, Fuzzy sets, Inf. Control 8(3), 1965 · R. Babuška, Fuzzy Modeling for Control, Springer, 2012 · D. E. Gustafson & W. C. Kessel, Fuzzy clustering with a fuzzy covariance matrix, IEEE CDC, 1979 · G. Sharma et al., The CIEDE2000 color-difference formula, CR&A 30(1), 2005 · K. B. Schloss, Color semantics in human cognition, CDPS 33(1), 2024.

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