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

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Abstract

Color–emotion correspondences play a crucial role in information visualization and affective communication, yet their systematic characterization remains challenging due to the inherent vagueness and interpersonal variability of emotional meaning. In this work, we investigate whether fuzzy logic systems trained from data can predict color–emotion associations using underlying emotional dimensions of valence, arousal, and dominance (VAD). Leveraging a psychophysical dataset in which participants associated colors with both emojis and their corresponding emotion labels, we construct interpretable Takagi–Sugeno fuzzy inference systems that map VAD coordinates to CIELAB color values. The models are trained using the fuzzy modelling and identification toolbox and evaluated using perceptual error measured by the CIEDE2000 color-difference metric. Results show that the fuzzy systems successfully capture global trends in the emotion–color relationship, producing smooth and coherent mappings across the VAD space for both concrete (emoji-based) and abstract (label-based) emotion representations. While prediction errors remain substantial due to subjectivity and variability in the data, vivid colors such as yellow and red are modeled more accurately than cooler tones, which exhibit greater emotional ambiguity. Overall, the findings demonstrate that data-driven fuzzy logic provides an effective and interpretable framework for modeling uncertain color–emotion correspondences, with potential applications in visualization design and affective computing.

Introduction

In the field of information visualization, color is an essential feature that facilitates visual reasoning. Effective visualizations employ color to guide intended inferences and to convey meaning about what is being shown. One strategy to accomplish this goal involves encoding information related to concepts with visual features (e.g., color) to facilitate interpretations of the concepts being visualized [1]. This is particularly effective when those concepts and visual features are semantically related. For instance, effective color encodings can be informed by color-concept correspondences, whereby using colors associated with the concepts being visualized improves inferences and understanding [2]. Therefore, color decisions in this context rely on knowledge about the extent to which colors might be generally associated with various concepts. Specific color-concept correspondences may be less intuitive particularly when the concepts being represented are more abstract (i.e., having little or no physical representation). For example, concepts related to emotion, such as 'anger' or 'happiness', tend to be relatively abstract, because they partly represent internal thoughts and feelings. Yet, people still hold robust patterns color-emotion associations, at least for emotion concepts that are frequently communicated [3]. Less research exists regarding color-emotion correspondences for more nuanced emotion concepts, which typically require lengthy psychophysical experiments. The purpose of the current research is to investigate the extent to which color-emotion correspondences can be predicted by fuzzy logic techniques that use logic rules determined from underlying emotion dimensions such as valence, arousal, and dominance (VAD).

The current approach employs a dataset evaluating colors that people associated with emojis, the emotion concepts (i.e., labels) those emojis represented, and their perceived underlying dimensions of valence, arousal, and dominance. Emojis are digital icons that are used to communicate about abstract emotion concepts through visual media [4]. While emojis comprise concrete facial expressions (e.g., smiles) and can be used to communicate emotion absent color, many emojis are often colored (e.g., red angry faces, green disgusted faces), suggesting that color information can meaningfully facilitate the digital communication of emotion. Therefore, we view the concrete nature of emojis used to convey abstract emotion concepts as a promising visual media to predict relevant color-emotion correspondences. Further, the current dataset separates color associations for emojis and their abstract concepts, which allows comparisons of the fuzzy logic approach in predicting color-emotion correspondences between both concrete and abstract emotion representations.

While fuzzy logic was developed a few decades ago as a tool to make computational human solution to problems expressed in liguistic implication rules, recently fuzzy logic systems built from data have proven to be a useful tool for finding relations between variables. In this work, we use trained fuzzy logic systems to find color-emotion associations that can contribute to both theory and applications.

In the next section we summarize the fundamentals of fuzzy logic and the tool used in this research. Later, methodology including dataset and fuzzy system training is explained which is followed by experimental results and conclusions.

Fuzzy logic and Fuzzy Modelling and Identification Toolbox (FMID)

Based on the definition of fuzzy sets by L.A. Zadeh [5], fuzzy logic was developed as a way to make computational algorithms expressed in linguistic implication rules given by human experts [6]. Traditionally, human knowledge was the base to develop fuzzy logic systems, but recently, due to the availability of much data but restricted knowledge, several tools have been developed to build fuzzy logic systems from data. In this way, fuzzy

logic can be used to infer knowledge from data as the built systems are interpretable [7].

The Fuzzy Modeling and Identification Toolbox (FMID) [8] is employed in this study. This toolbox enables the construction of a fuzzy logic rule-based system capable of determining the *VAD* (Valence, Arousal, Dominance) coordinates to reproduce a target color associated with said emotional coordinates.

In this work, the Fuzzy Modeling and Identification Toolbox (FMID) [8] is used to develop a Takagi-Sugeno (TS) fuzzy inference system (FIS). This type of systems are charachterized for having linguistic variables in the antecedent of each rule and a function to compute the output from the inputs in the corresponding consequent. FMID provides flexibility in parameter configuration depending on the application. Once the dataset is introduced, the toolbox applies fuzzy clustering—controlled by a user-defined overlap degree—to partition the data into a predefined number of clusters. Because the fuzzy rules are derived directly from these clusters, the user must specify beforehand the number of clusters, which corresponds to the number of local submodels in the FIS.

To perform clustering, the Gustafson-Kessel (GK) algorithm [9] is utilized, as it is widely adopted in fuzzy clustering tasks. This algorithm determines the data partitioning and defines the antecedent membership functions. Subsequently, the consequent functions are estimated using least squares minimization. Several types of consequent functions can be evaluated, and the most suitable choice depends on the characteristics of the dataset and the problem under study.

After configuring and initializing all FMID parameters, the model is validated using the test set. The trained system takes *VAD* coordinates as input and predicts the corresponding $L^*a^*b^*$ values. Model performance can be quantified using the mean squared error between predicted and reference $L^*a^*b^*$ values ($MSE_{L^*a^*b^*}$), which is useful during parameter tuning. Nevertheless, the ultimate evaluation should consider the perceptual difference between the predicted colors and the reference colors, calculated in terms of ΔE_{00} visual error.

Three key parameters that significantly influence $MSE_{L^*a^*b^*}$ and the interpretation are analyzed: (1) the number of clusters (rules), and (2) the overlap parameter m, which controls the fuzziness of the clustering. The impact of the number of clusters and the overlap parameter m is studied. The number of clusters is varied from 3 to 5, while m is adjusted within the range of 1.05 to 2. Selecting the appropriate number of clusters involves a trade-off. Increasing the number of clusters generally improves performance, approaching optimal results, but also increases model complexity and likelihood of overfitting. On the other hand, a slight reduction in the number of clusters leads to only minor performance degradation while producing a simpler and more interpretable model.

Methodology

The methodology adopted in this study follows a structured workflow. First, the data were preprocessed and prepared for modeling. Subsequently, the processed dataset was used to train the fuzzy model, enabling the system to learn the relationship between the input *VAD* coordinates and the output $L^*a^*b^*$ coordinates.

Dataset

The current dataset comes from a separate psychophysical experiment that evaluated color associations for emojis, the concepts they represent, and ratings of valence, arousal, and dominance. In the experimental procedure, 78 participants saw 22 emojis and completed 3 separate tasks: Emoji-Color, Label-Color, and Emotion-Rating. In the Emoji-Color task, participants viewed each of the emojis and were asked to "Pick the color that you associate with this emoji", from a color grid that spanned CIELAB L* (lightness), a* (red-green), and b* (yellow-blue) dimensions. In the Label-Color task, participants viewed each of the emojis and were asked to "Enter a label to describe the meaning of that emoji", which was a free-text response. Then, participants viewed their text-responses and were asked to "Pick the color that you associate with this concept", from a similar color grid as used in the Emoji-Color task. In the Emotion-Rating task, participants viewed each of the emojis and were asked to rate them along scales corresponding to valence (e.g., positive to negative), arousal (e.g., active to inactive), and dominance (e.g., dominant to submissive).

Fuzzy system training

The fuzzy inference system was trained using the FMID toolbox. For this purpose, the dataset was preprocessed so that the input variables correspond to the *VAD* coordinates, while the output variables are the corresponding CIELAB ($L^*a^*b^*$) color coordinates.

During the training process, several configurations were evaluated by varying two main parameters: the number of clusters (which determines the number of fuzzy rules) and the fuzzification parameter m. Although different configurations were studied ($n_{\text{clusters}} \in \{3,4,5\}$ and $m \in \{1.25, 1.5, 1.75\}$), no significant improvement in the Mean Squared Error (MSE) was observed across the tested settings. Therefore, the final model selection was guided primarily by interpretability rather than purely by error minimization. Thus, the final configuration was set to three clusters (three fuzzy rules) and a overlapping parameter value of $m = 1.5$.

Results

The results of the fuzzy inference system are examined with particular attention to the learned rule base and the relationship between the *VAD* input space and the corresponding $L^*a^*b^*$ outputs and, for that, we need to carefully analyze the three implication rules found in the training. This interpretation provides insight into how different regions of the *VAD* space are associated with specific color responses in the $L^*a^*b^*$ domain.

Subsequently, the model predictions are represented within the *VAD* space, enabling a direct comparison with the reference data. This allows for an assessment of how well the system captures the underlying relationships between emotional variables and color representations.

In addition, the performance of the model is quantitatively evaluated using the ΔE_{00} color difference metric. To further support this analysis, the errors are visualized in a three-dimensional representation, where lower errors are depicted in green and higher errors in red, providing an intuitive overview of the model's accuracy across the space.

Rule interpretation

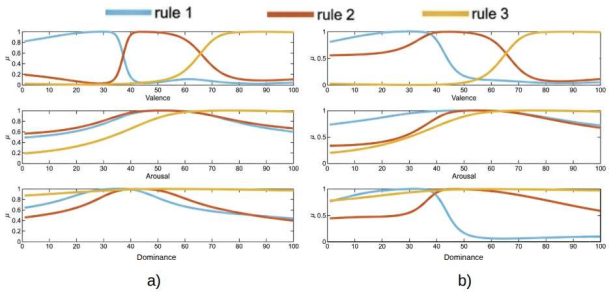

Figure 1. *Membership functions of the fuzzy systems of the emojis (left) and the labels (right). There is one membership function per variable for each of the clusters.*

Table 1. Consequent functions for emojis and labels. Each rule has three consequents, one for each output variable. When combined, these outputs define the color associated with the corresponding VAD values within their antecedent intervals.

Rule	Emojis	Labels
1	$L_1 = 0.39v - 0.024a - 0.19d + 55$	$L_1 = 0.26v + 0.0012a - 0.10d + 47$
	$a_1 = -0.6v - 0.089a + 0.81d + 12$	$a_1 = 0.02v - 0.20a - 0.055d + 20$
	$b_1 = 0.13v + 0.0066a + 0.63d - 19$	$b_1 = 0.85v - 0.17a - 0.45d + 5.1$
2	$L_2 = 0.21v + 0.023a - 0.0038d + 58$	$L_2 = 0.46v + 0.13a - 0.057d + 33$
	$a_2 = 0.044v + 0.29a - 0.3d - 0.55$	$a_2 = -0.63v + 0.43a - 0.034d + 15$
	$b_2 = -0.097v + 0.6a - 0.026d + 8.5$	$b_2 = -0.27v + 0.97a + 0.035d - 29$
3	$L_3 = 0.066v - 0.095a + 0.029d + 79$	$L_3 = 0.067v - 0.12a + 0.031d + 75$
	$a_3 = -0.051v + 0.12a - 0.048d + 7.7$	$a_3 = 0.31v + 0.09a - 0.030d - 16$
	$b_3 = 0.37v - 0.40a - 0.074d + 59$	$b_3 = 0.027v - 0.30a + 0.12d + 58$

Trained rules information is shown in Figure 1 (rule antecedents) and Table 1 (rule consequents). The interpretation of a fuzzy system is based on the joint analysis of its membership functions (antecedents) and its consequent functions within the rule base. The membership functions first map each input variable—such as VAD (valence, arousal, dominance)—into degrees of membership over linguistic terms, effectively defining fuzzy intervals rather than crisp thresholds. For a given input, each VAD tern activates one or more membership functions to different degrees, producing a set of membership grades that quantify how strongly the input belongs to each linguistic label and, unltimately, how much each consequent function will weigh when computing the system output.

These membership degrees are then used in the inference process to evaluate the rules. Each rule contributes a consequent output (e.g., $L^*a^*b^*$ color values), which is weighted by its firing strength. The final output is obtained by aggregating all rule contributions, effectively combining the overlapping fuzzy intervals of the VAD space into a single crisp output in the $L^*a^*b^*$ color space. In this way, the system interprets continuous emotional input by blending local rule responses into a smooth, interpretable mapping between VAD values and perceived color.

Our objective is to analyze the structure of the rules beyond their numerical form, understanding how each rule encodes a specific relationship within the emotional inference process. To this end, the behavior of each rule is visualized, as shown in Figure 3. The resulting plots illustrate how the output varies as the VAD variables change across their corresponding membership function intervals, highlighting the sensitivity of each rule to variations in the input space.

By jointly analyzing Figures 1 and 3 and Table 1 we can interprete the following: (i) the main variable that determines which rule to use in valence, as it is the one that less overlaps among the rules membership funtion; (ii) for the labels dataset, arousal has a more important role in choosing the rule than for the emojis one; (iii) valence is as well the most important variable when determining the output color as it is associated with the highest coefficients in Table 1. By looking at the colors generated by each rule in Figure 3 we can see that for both emojis and labels we have two similar rules (2-3) that generate either yellow colors or dark colors while the other rule accounts for colors from dark to red in different degrees. Yellow colors are associated, through rule 3, to higher values of valence and arousal while darker colors are associated, through rule 1 to lower values of valence and arousal.

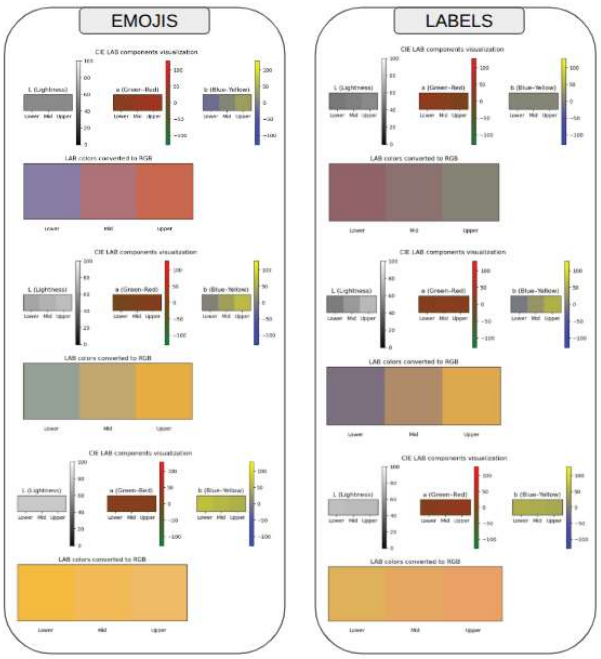

Figure 3. *Visualization of fuzzy rule behavior across the input space. For each VAD dimension (valence, arousal, and dominance), the lower, medium, and upper bounds of the corresponding membership functions are evaluated, and the resulting output is represented in the LAB color space. The figure illustrates how the LAB coordinates evolve as the input variables vary within their respective fuzzy intervals.*

The rules, when combined, take VAD values as input and produce $L^*a^*b^*$ values as output. Consequently, the system can be used to predict and visualize the mapping within the VAD space, allowing the general trends of the color–emotion relationship captured by the fuzzy model to be observed. Since the model is designed to represent overall patterns rather than individual instances, outliers and highly specific cases are not explicitly cap-

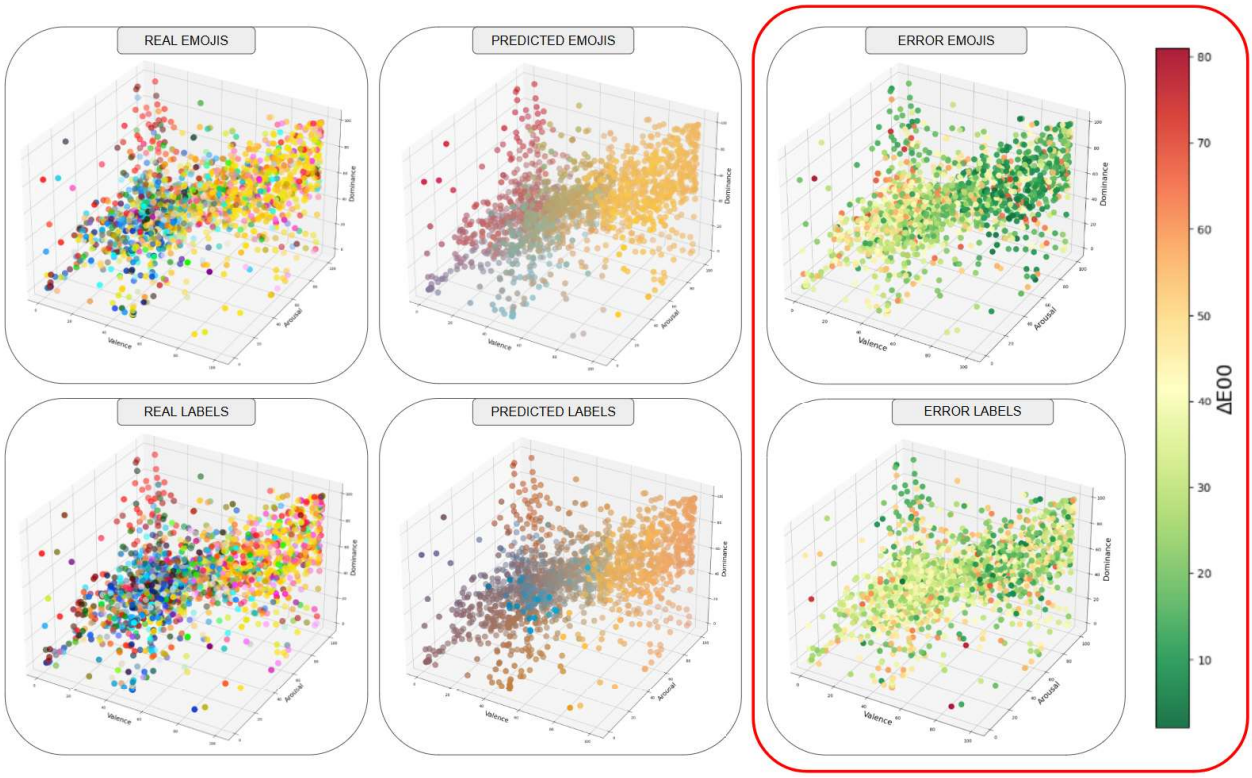

Figure 2. *Real vs. predicted colors in the VAD space for emojis (top row) and labels (bottom row), showing ground truth, predictions, and errors (left to right).*

tured. As a result, Figure 2 shows a smoother and more generalized distribution of colors. In the left panels (Real Emojis and Real Labels), the data exhibit a highly scattered and heterogeneous distribution, reflecting the natural variability and noise present in the original samples. The relationship between Valence, Arousal, and Dominance is present but not clearly structured, with significant overlap between regions and noticeable dispersion across the space.

In contrast, the right panels (Predicted Emojis and Predicted Labels) show the corresponding outputs produced by the fuzzy systems. These results are considerably smoother and more structured, indicating that the models have captured the underlying global trends in the VAD color/emotion relationship. Both fuzzy systems (for emojis and labels) are able to capture the global structure of the data and provide interpretable, visually coherent mappings in the VAD space, although with limited precision at the level of individual samples. The fuzzy inference process effectively interpolates between regions of the input space, producing continuous transitions rather than discrete or highly scattered points.

Overall, we can see yellow colors associated to high values of all variables, red colors for low valence and high arousal and dominance and dark colors to low values of all variables. Intermediate values of the variables are more difficult to associate to colors, as can be seen in the left panels. The fuzzy model tends to provide blueish colors as a general trend but it can be seen that the highest errors are found for that regions.

The predicted regions can be summarized as in Table 2. This table serves as a compact representation of how the fuzzy systems partition the emotional space into interpretable regions, making explicit the underlying structure captured in the predicted distributions.

Table 2. Summary of the fuzzy system partition of the VAD space.

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

Error quantification and visualization

The color difference between two colors in the CIELAB space is measured using the CIEDE2000 metric, denoted as ΔE_{00} [10]. This metric improves perceptual uniformity by accounting for differences in lightness, chroma, and hue.

Table 3. Errors in terms of ΔE_{00} of the emojis and labels models in the training and test sets.

		Emojis		Labels	
	count	mean	std	mean	std
Train	1225	29.93	15.48	33.06	11.96
Test	523	30.75	15.74	32.78	12.26

The average and standard deviation of errors for both the

training and test sets are reported in Table 3. The relatively high error values are likely attributable to substantial interpersonal variability, as well as individual preferences and inherent biases in the data.

To better understand the error distribution and assess whether certain regions of the VAD space are more difficult to model, the errors were visualized, as shown in Figure 2. As observed, regions associated with higher VAD values are captured more accurately by both fuzzy systems, with particularly strong performance in the emoji-based model. In contrast, the central region of the space appears to be the most challenging to model, likely due to the higher levels of uncertainty and ambiguity present in this area.

If we examine which colors are better or worse predicted by the emoji and label models, Figures 4 and 5 provide a clear comparison. In both cases, more vivid colors such as yellow and red are predicted with higher accuracy.



Figure 4. *Best (left) and worst (right) predictions of the emojis.*

In contrast, blue and green tones tend to be mispredicted. The emoji-based model generally shifts these colors toward more yellowish tones, whereas the label-based model tends to produce pinkish hues. This behavior is likely influenced by the distribution of colors in the central region of the VAD space for the labels, where mixtures of blue and red are more prevalent, leading to this bias in the predicted outputs.



Figure 5. *Best (left) and worst (right) predictions of the labels.*

Overall, both models capture the general trends between the VAD dimensions and color, with the emoji-based system showing a slightly better fit to the underlying distribution. In particular, they perform well in predicting vivid and perceptually salient colors such as yellow and red, which are associated with higher arousal and more clearly defined emotional profiles. These colors tend to occupy more distinct regions in the VAD space, making them easier for the models to learn and reproduce.

In contrast, cooler tones such as green and blue are more difficult to model accurately. These colors often span broader and less well-defined regions in the VAD space, as their emotional interpretation varies significantly depending on hue, saturation, and context. This variability is especially evident in the central regions of the VAD space, where emotional states are less intense and more diffuse, making predictions less precise and increasing the overall error.

Discussion and conclusions

This study explored the use of data-driven fuzzy logic systems to model and predict color–emotion correspondences based on the valence, arousal, and dominance dimensions of emotion. By training Takagi–Sugeno fuzzy inference systems on a psychophysical dataset linking VAD ratings to CIELAB color coordinates, we demonstrated that fuzzy models can recover meaningful and interpretable relationships between emotional dimensions and perceived color. Importantly, the learned rule bases offer insight into how different regions of the emotional space are associated with characteristic color tendencies, highlighting valence as a dominant factor in rule activation and color prediction.

The results show that the trained fuzzy models are able to capture the general trends underlying the relationship between emotion and color rather than making precise predictions for individual samples. In particular, both systems provide coherent and interpretable mappings in the VAD space, reflecting meaningful structures that align with known patterns in color perception. However, the $\Delta E00$ error remains relatively high, which can be attributed to the inherent variability and subjectivity of the task. As it can be seen in Figure 2, the predicted colors are predominantly low-saturation, yellowish hues, contrasting with the vivid colors of the corresponding emoji stimuli. Emotional perception of color is highly context-dependent, and individual differences introduce significant dispersion that limits the precision achievable at the level of specific samples. Additionally, a noticeable bias appears in the case of yellow. When participants are uncertain, they tend to select yellow more frequently, likely due to their familiarity with emojis, which are commonly represented in this color. This suggests that learned conventions and exposure can influence responses beyond purely perceptual factors. Furthermore, while some colors occupy well-defined regions in the VAD space, others—such as green or blue—span a broader range depending on their hue and saturation, allowing them to convey different emotional states. This variability reinforces the idea that certain colors are more flexible in their emotional associations.

Collectively, these findings highlight the complexity of the emotion–color relationship and point to the need for further research to better understand its underlying mechanisms. In this regard, fuzzy systems constitute an appropriate methodological framework for capturing and modeling the inherent variability and uncertainty associated with this relationship.

Overall, this work supports the suitability of fuzzy logic as a methodological framework for studying color–emotion relationships, where ambiguity and gradual transitions are intrinsic. Future work could extend this approach by incorporating additional emotional dimensions, contextual variables, or adaptive fuzzy structures, as well as by integrating perceptual weighting or probabilistic components to further account for uncertainty. Such extensions may enhance the applicability of fuzzy color–emotion models in visualization, human–computer interaction, and affective design.

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