Affective Color Palette Recommendations with Non-negative Tensor Factorization

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- Related Work
- Non-Negative Factorization
- Composing The Rating Tensor
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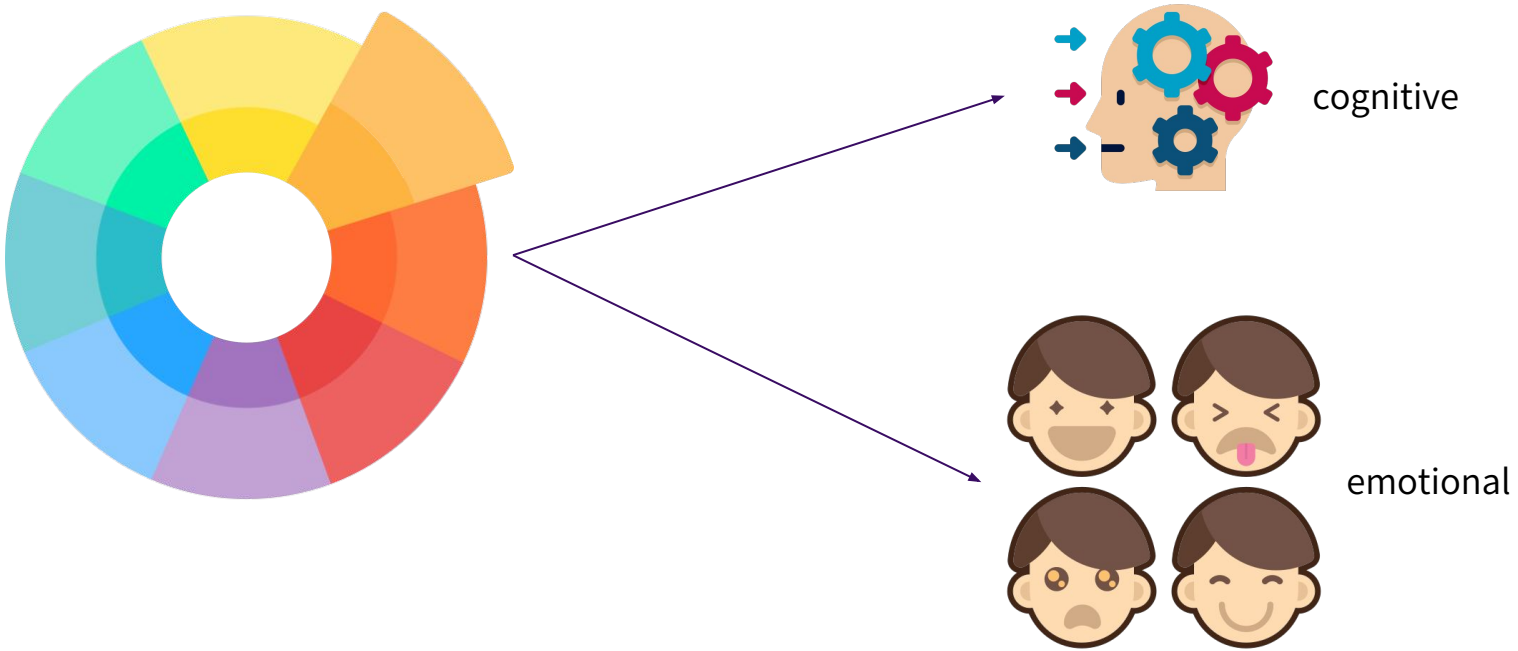
Introduction

Color is a crucial element in visual media, influencing both cognitive and emotional perceptions.



How color influences visual media and emotions

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The challenge

Emotional Factors

Individual Preferences

Color Palettes

Non-Negative Tensor Factorization (NTF)

to implement a color palette recommendation system considering both individual preferences and affective intentions

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Related Work

A. Color Harmony Design

Researchers have been studying how colors work together, both in theory and in real-world applications.

a. ***Ou et al.*** started with models for harmonizing two colors and expanded to three.
b. ***Cohen-Or*** and others began enhancing color harmony in images using computer graphics
c. ***Wang*** and their team built a system that follows specific *design rules* for colors. This system can automatically choose colors that are sensible and meaningful, especially when dealing with data visualization.
d. ***Lindner*** and colleagues even made a computer model associating colors with words, creating color palettes based on language.

L.-C. Ou and M. R. Luo, “A colour harmony model for two-colour combinations,” Color Research & Application doi: 10.1002/col.20208
D. Cohen-Or, O. Sorkine, R. Gal, T. Leyvand, and Y.-Q. Xu, “Color harmonization,” ACM Transactions on Graphics doi: 10.1145/1141911.1141933
L. Wang, J. Giesen, K. T. McDonnell, P. Zolliker, and K. Mueller, “Color design for illustrative visualization,” IEEE Transactions on Visualization and Computer Graphics doi:10.1109/TVCG.2008.118
J. Lindner and S. Susstrunk, “Automatic color palette creation from words,” in Proceedings of the IS&T 21st Color and Imaging Conference, [Online]. Available: https://library.imaging.org/cic/articles/21/1/art00012

Related Work

B. Tools for Color Design

Tools have been made to make colors look better using advanced techniques:

a. ***ColorBrewer*** **:** Choose appealing color combinations, especially for maps.
b. ***Setlur et al.*** **:** Aims to make colors relevant and purposeful based on the content they represent.
c. ***Fang et al.*** **:** Developed an algorithm to arrange colors to better distinguish visual elements.
d. ***Smart et al.*** **:** Study how designers use color in lamps with machine learning.
e. ***Misue*** : Improve understanding of color differences, using contours and color ramps.

M. Harrower and C. A. Brewer, “Colorbrewer.org: An online tool for selecting colour schemes for maps,” The Cartographic Journal. doi: 10.1179/000870403235002042
V. Setlur and M. C. Stone, “A linguistic approach to categorical color assignment for data visualization,” IEEE Transactions on Visualization and Computer Graphics, doi: 10.1109/TVCG.2015.2467471
H. Fang, S. Walton, E. Delahaye, J. Harris, D. A. Storchak, and M. Chen, “Categorical colormap optimization with visualization case studies,” IEEE Transactions on Visualization and Computer Graphics, doi: 10.1109/TVCG.2016.2599214
S. Smart, “Color crafting: Automating the construction of designer quality color ramps,” IEEE Transactions on Visualization and Computer Graphics, doi: 10.1109/TVCG.2019.2934284
K. Misue, “Development of a tool to help understand color spaces and color differences,” IV2020, doi: 10.1109/IV51561.2020.00096

Related Work

C. Recommendation systems

a. ***Collaborative filtering*** **:** predicts a new user's favorites by simulating the behavior of similar existing users.
b. ***Color Palette Recommendation Systems*** **:**
    i. *O'Donovan* : predicted what colors people like by studying a big dataset of rated color themes.
    ii. *Linping* : created a smart system using deep learning to recommend color palettes based on data.

R. Chen, Q. Hua, Y.-S. Chang, B. Wang, L. Zhang, and X. Kong, “A survey of collaborative filtering-based recommender systems: From traditional methods to hybrid methods based on social networks,” IEEE Access,doi: 10.1109/ACCESS.2018.2877208
P. O’Donovan, A. Agarwala, and A. Hertzmann, “Collaborative filtering of color aesthetics,” in Proceedings of the Workshop on Computational Aesthetics (CAe’14), doi: 10.1145/2630099.2630100
L. Yuan, Z. Zhou, J. Zhao, Y. Guo, F. Du, and H. Qu, “Infocolorizer: Interactive recommendation of color palettes for infographics,” IEEE Transactions on Visualization and Computer Graphics, 2021. doi: 10.1109/TVCG.2021.3085327

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Non-negative Matrix Factorization (NMF)

- Co-occurrence matrix
- Non-negative factorization maximally respects the **underlying sparsity** in the elements of the factor matrices.
- minimizing the error **|| V − W H ||**

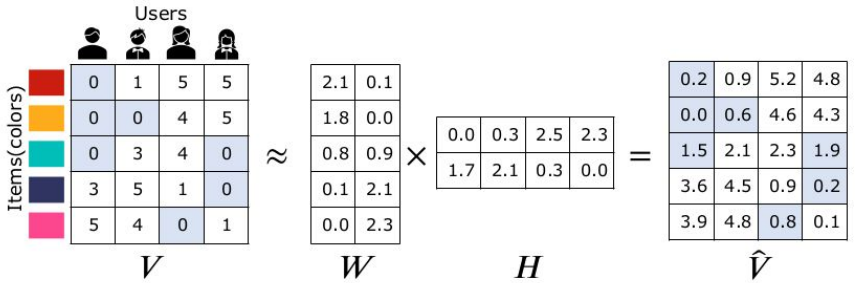

Fig. 2. NMF lets us factorize a data matrix $\boldsymbol{V}$ into matrices $\boldsymbol{W}$ and $\boldsymbol{H}$. $\widehat{\boldsymbol{V}}$ is the reconstructed matrix as the product of $\boldsymbol{W}$ and $\boldsymbol{H}$ and approximates the original matrix $\boldsymbol{V}$.

Non-negative Tensor Factorization (NTF)

- $\boldsymbol{X} \approx \widehat{\boldsymbol{X}} = \boldsymbol{A} \otimes \boldsymbol{B} \otimes \boldsymbol{C}.$
- minimizes the error **|| X − A ⊗ B ⊗ C ||**

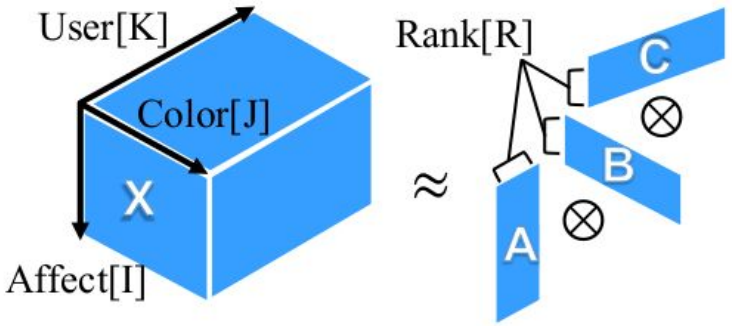

Fig. 3. NTF allows us to factorize a tensor $\boldsymbol{X}$ into the three factor matrices $\boldsymbol{A}$, $\boldsymbol{B}$, and $\boldsymbol{C}$.

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Choice of Affects and Colors

- Affective Color in Visualization (Bartram et al.)
- **Color: 41**
- **Affect: 8**
  - Positive, Negative, Calm, Exciting, Serious, Playful, Trustworthy, and Disturbing

Fig. 4. The set of 41 representative color samples proposed in [23]. Color IDs are used consistently in this manuscript.

Collecting Color Scores in the Online Questionnaire

- **User: 50**
  - 12 females and 38 males
  - ages ranged from 19 to 64
- We asked participants to select **five colors** out of the 41 representative color samples for each of the eight affective categories.
- We assigned the scores **5–1** to the five selected colors in that order and **0** to the other unselected colors.

Collecting Color Scores in the Online Questionnaire

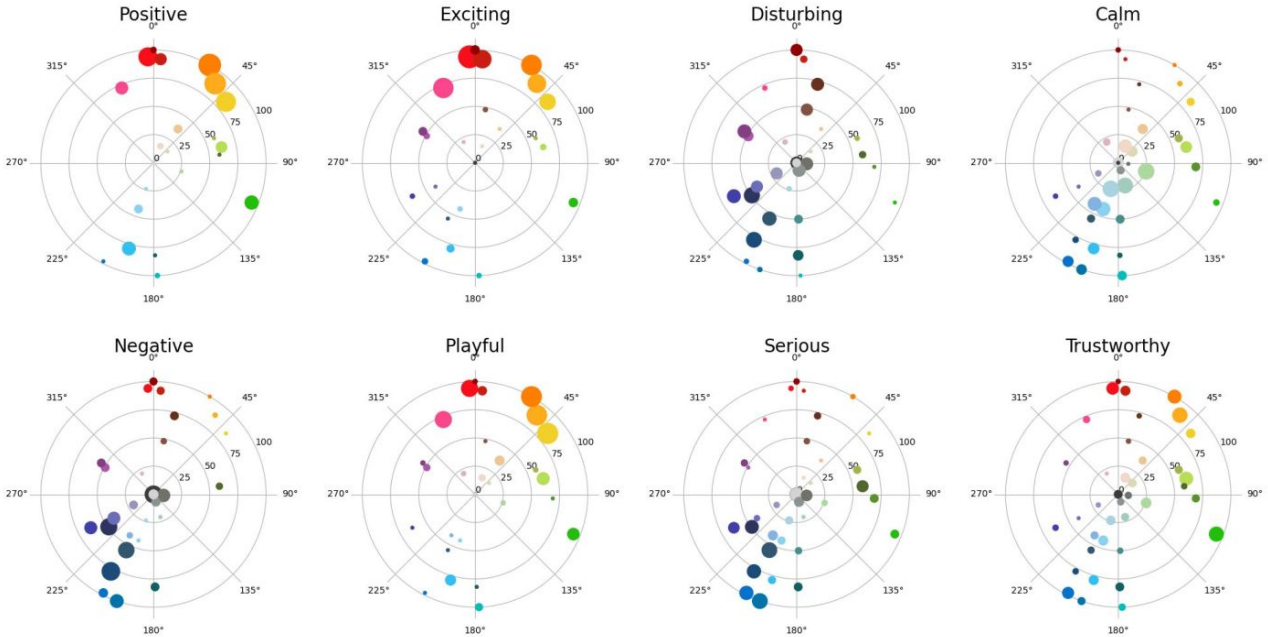
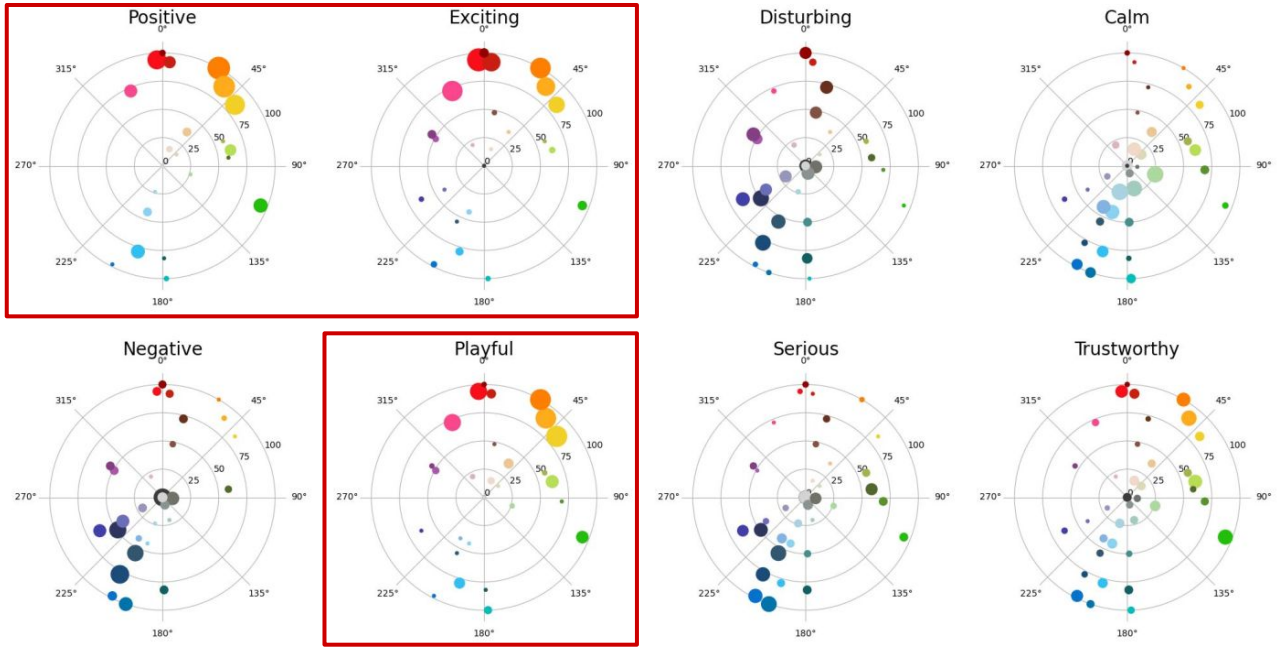


Fig. 5. Colors selected for each affect in the questionnaire. Each color sample is plotted on a hue wheel, while the distance from the center corresponds to the saturation. The size of each dot indicates the selection frequency of the corresponding color.

Collecting Color Scores in the Online Questionnaire



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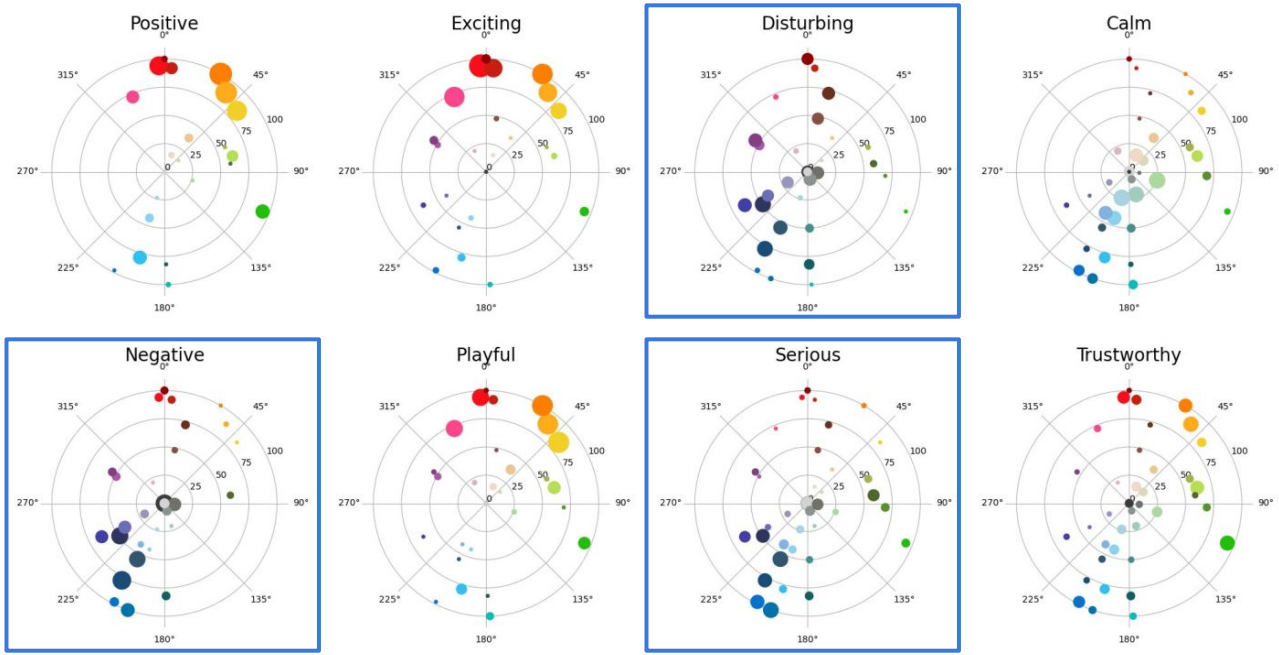

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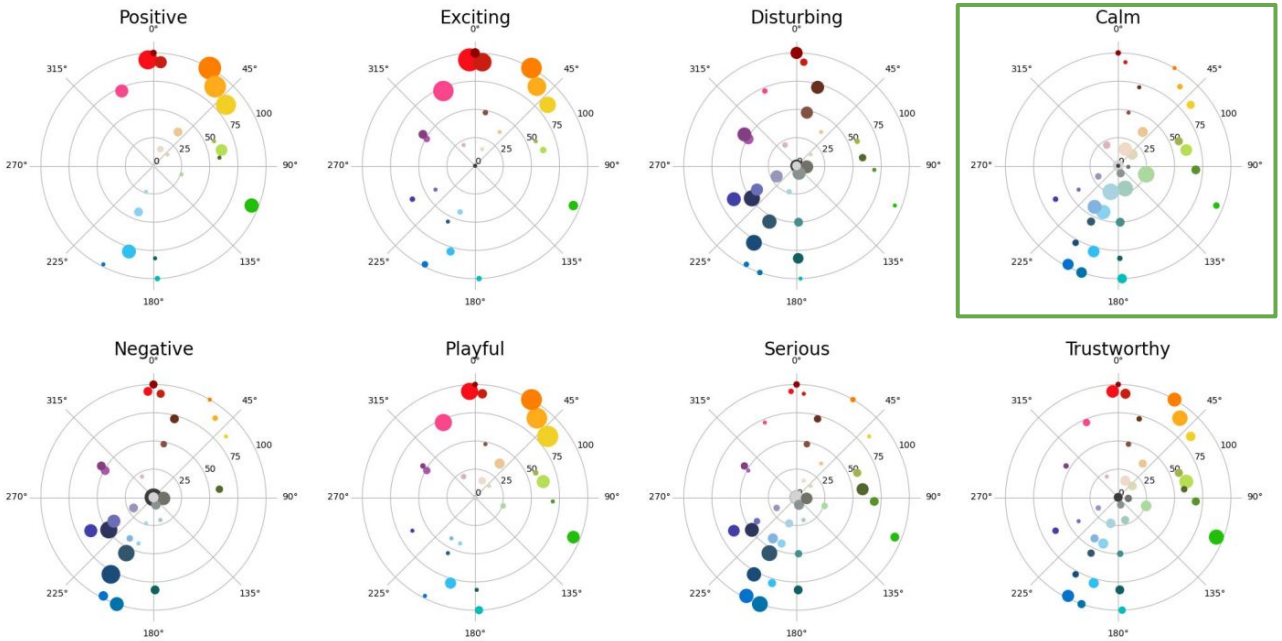

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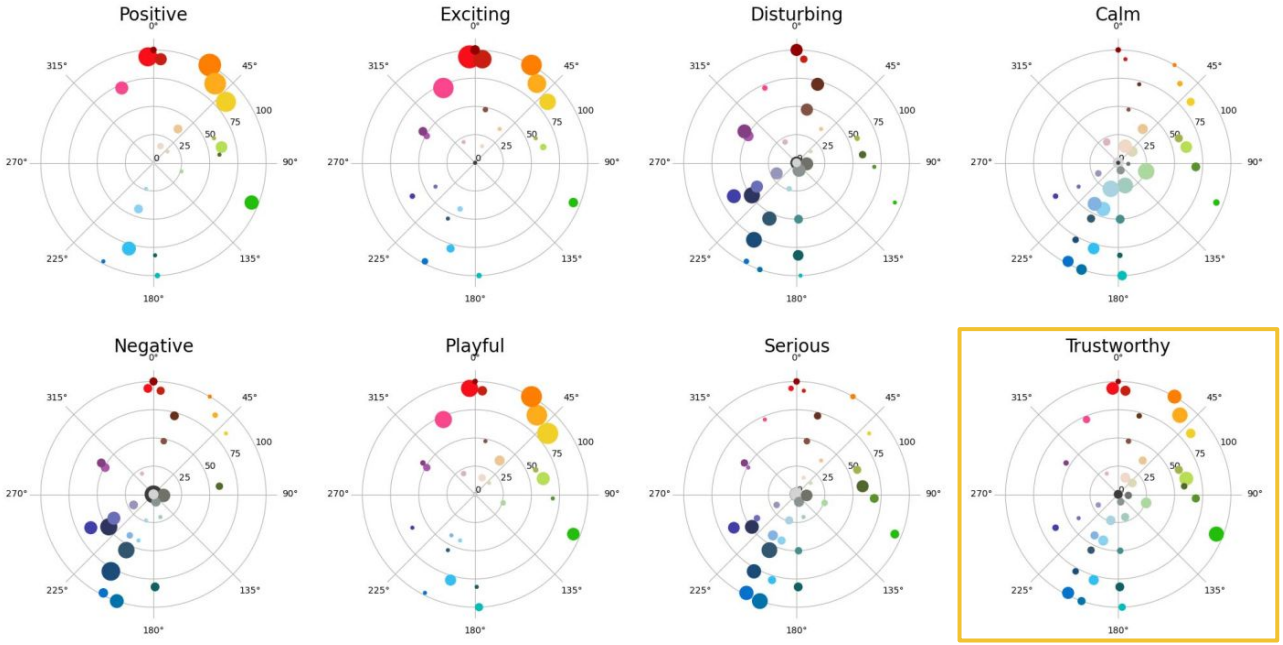

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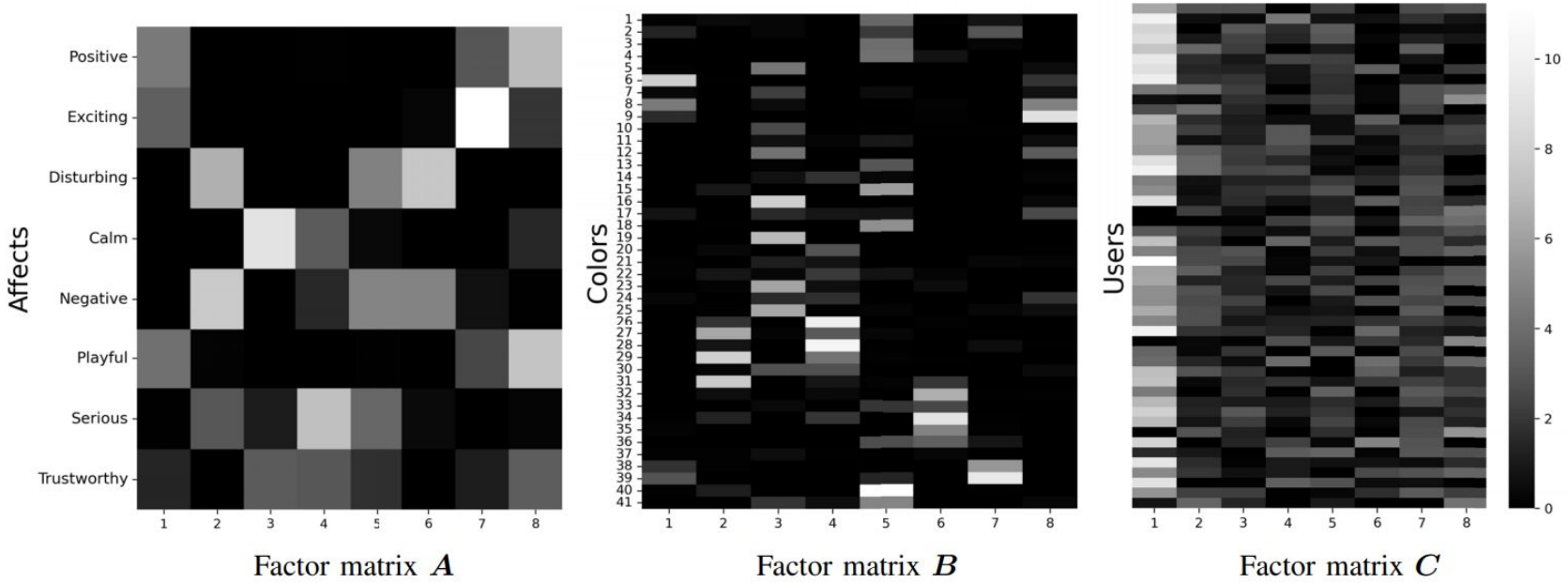
Result

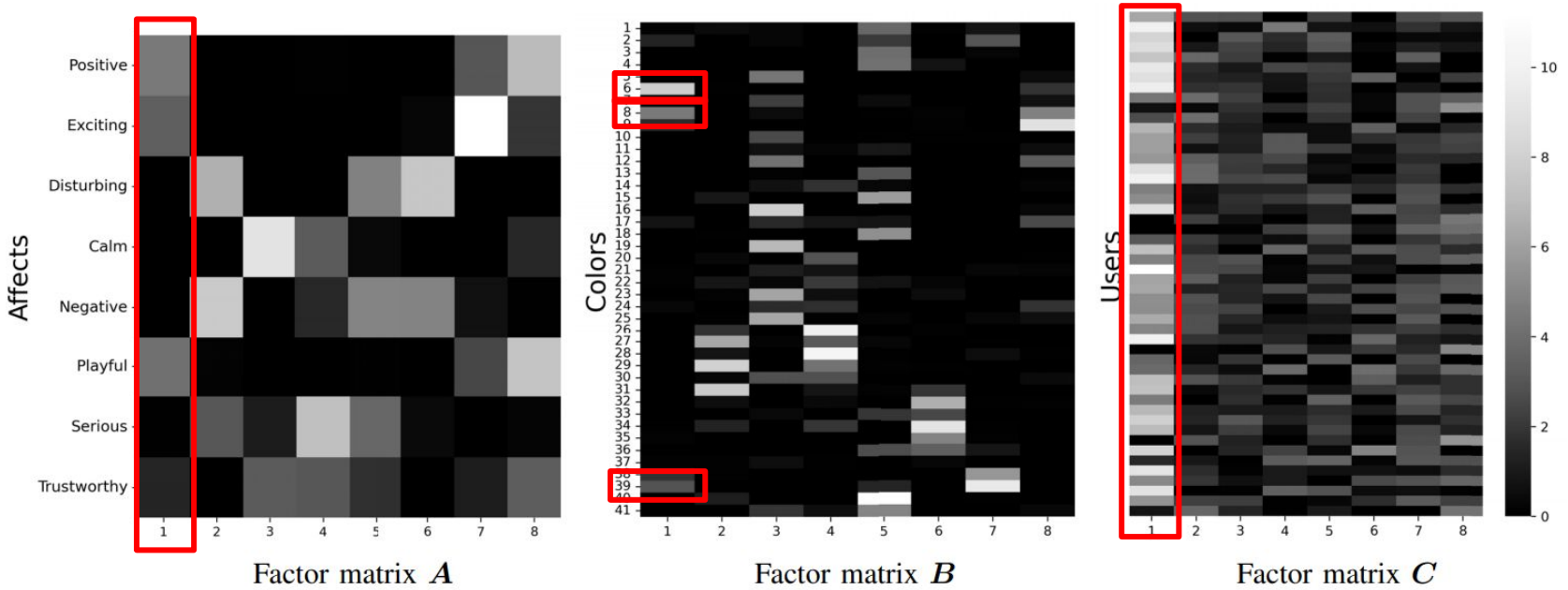
Selecte basis factors R = 8 because this choice maximally retained important trends in the color selection.

Affect: 8 **Color: 41** **User: 50**



Result


(40) (37) (34) (31) (28) (25) (22) (19) (16) (13) (10) (7) (4) (1)
(41) (38) (35) (32) (29) (26) (23) (20) (17) (14) (11) (8) (5) (2)
(39) (36) (33) (30) (27) (24) (21) (18) (15) (12) (9) (6) (3)


Affects
Positive
Exciting
Disturbing
Calm
Negative
Playful
Serious
Trustworthy
1 2 3 4 5 6 7 8
Factor matrix A
Colors
1 2 3 4 6 8 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 39 41
1 2 3 4 5 6 7 8
Factor matrix B
Users
1 2 3 4 5 6 7 8
Factor matrix C
10
8
6
4
2
0

Result


(40) (37) (34) (31) (28) (25) (22) (19) (16) (13) (10) (7) (4) (1)
(41) (38) (35) (32) (29) (26) (23) (20) (17) (14) (11) (8) (5) (2)
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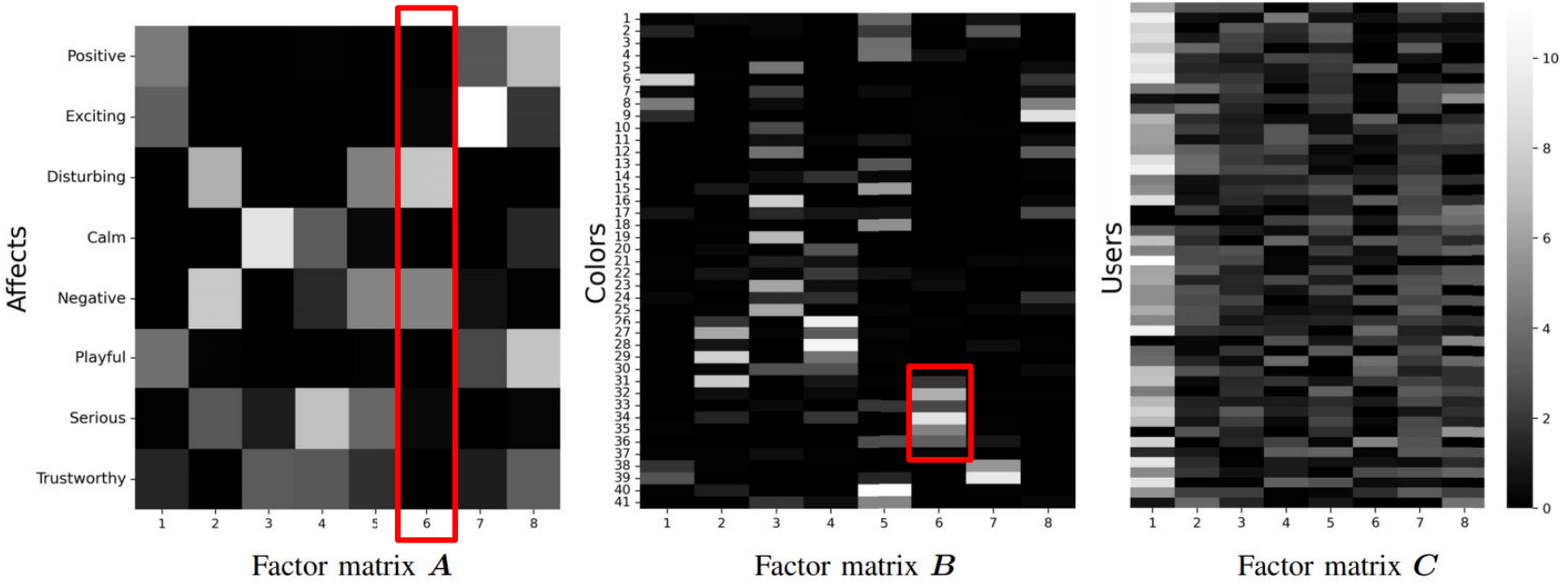
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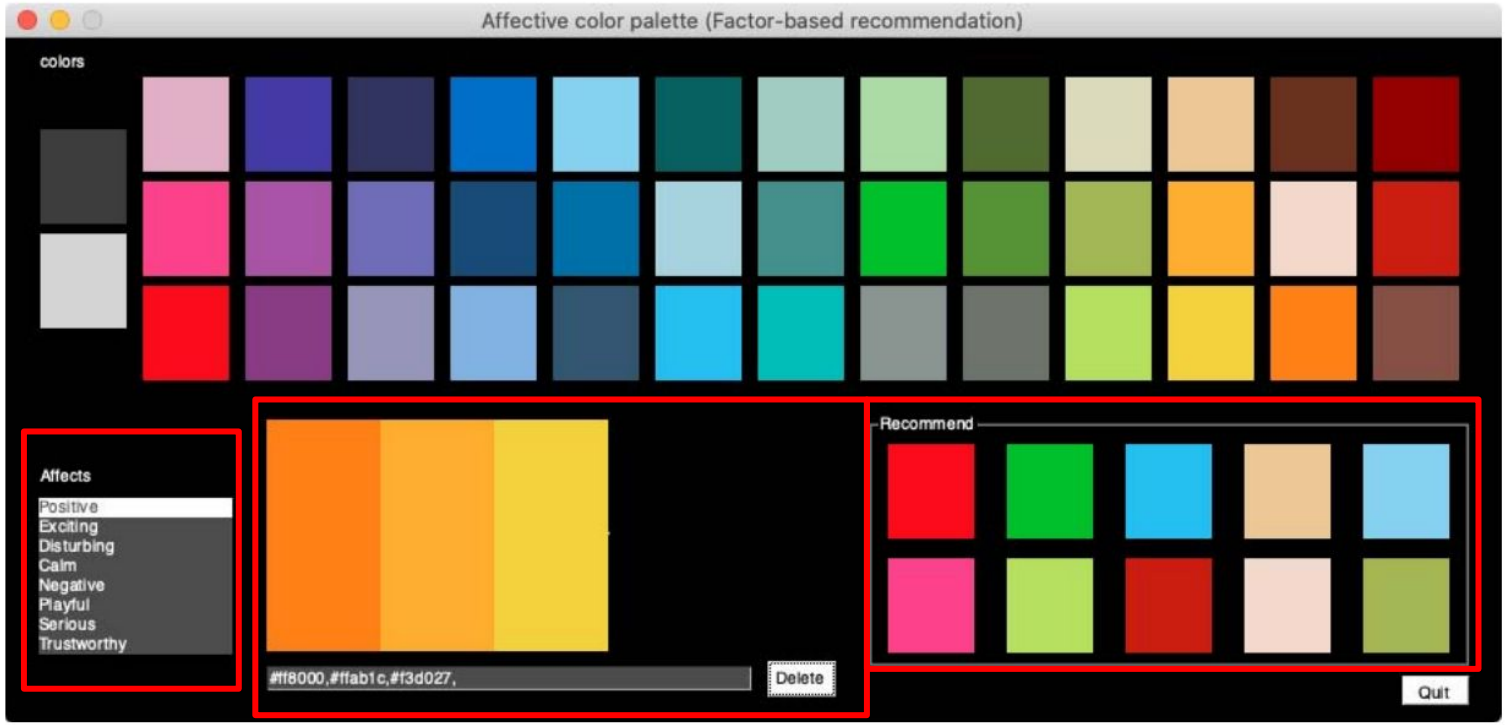
1 2 3 4 5 6 7 8
Factor matrix A
Colors
1 2 3 4 5 6 7 8
Factor matrix B
Users
1 2 3 4 5 6 7 8
Factor matrix C
10
8
6
4
2
0

Result

Case I: Predicting colors individually for each affective category



Result

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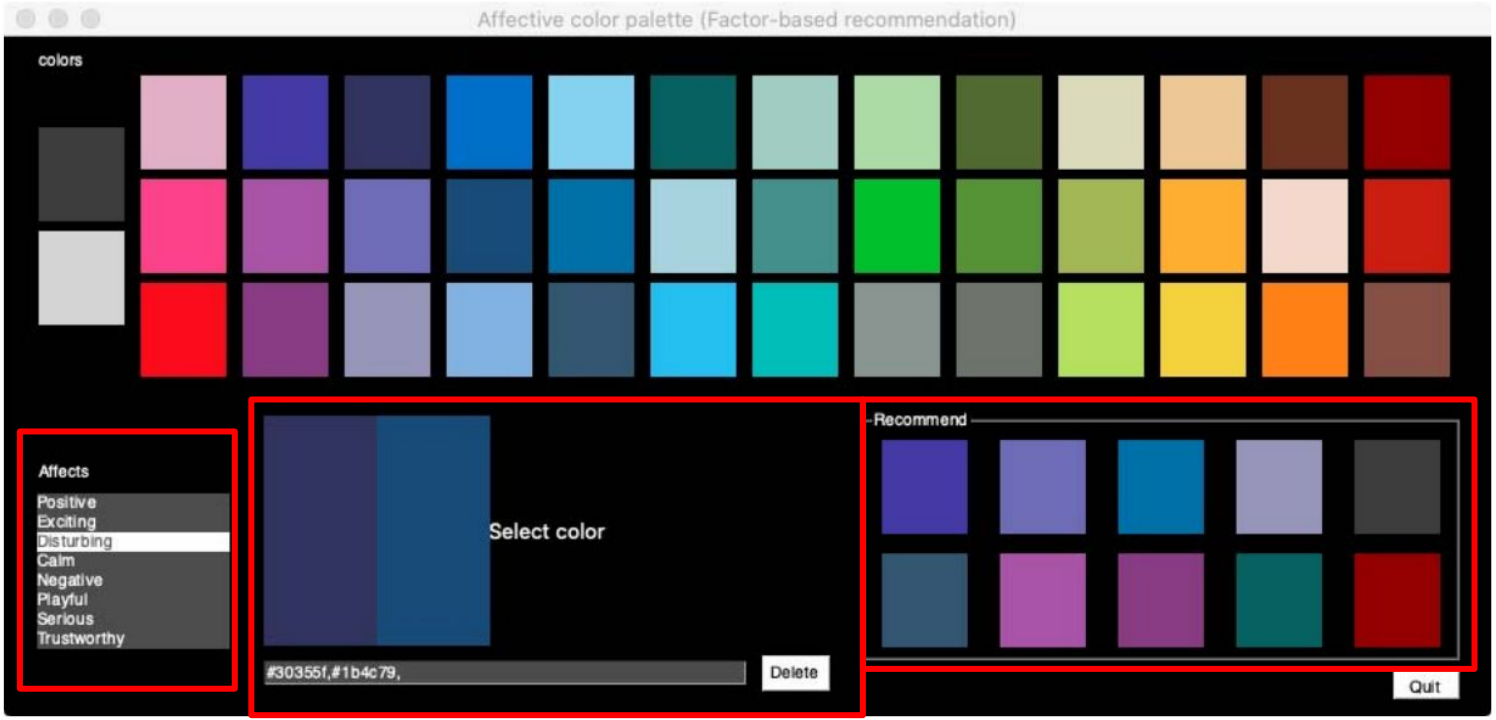
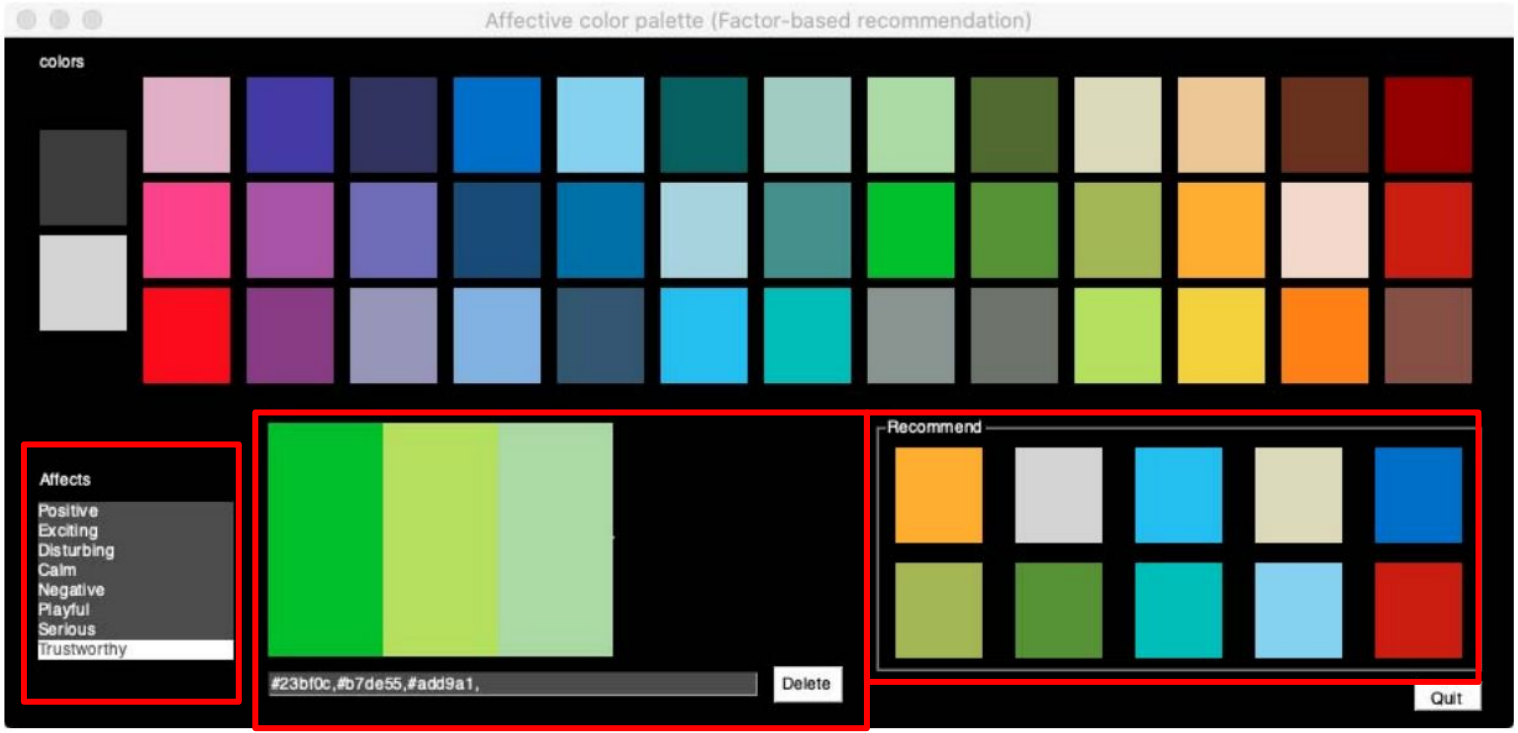


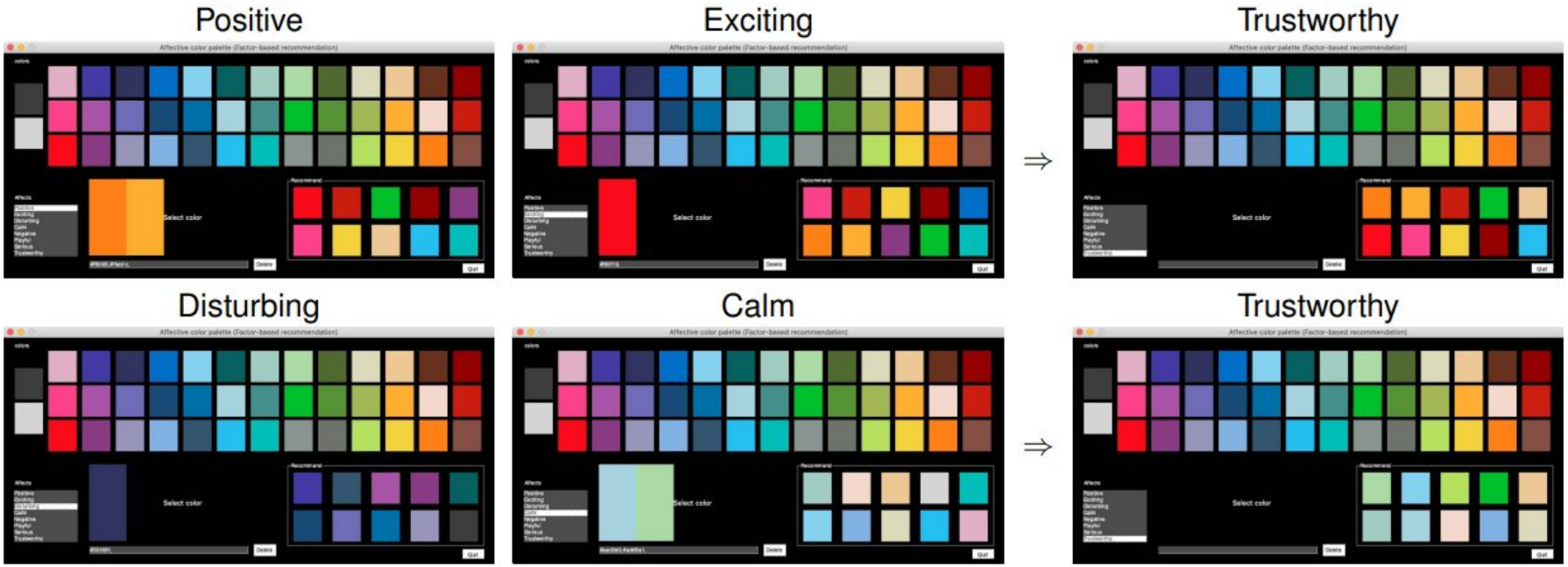
Result

Case I: Predicting colors individually for each affective category



Result

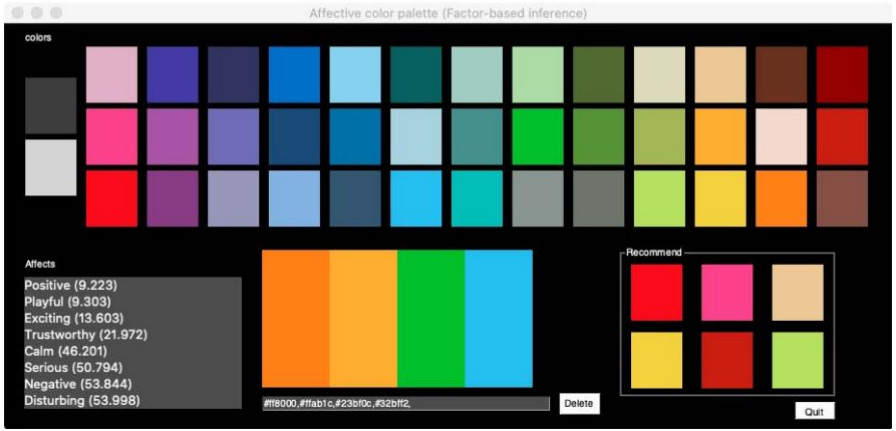
Case II: Predicting colors taking all affective categories into account



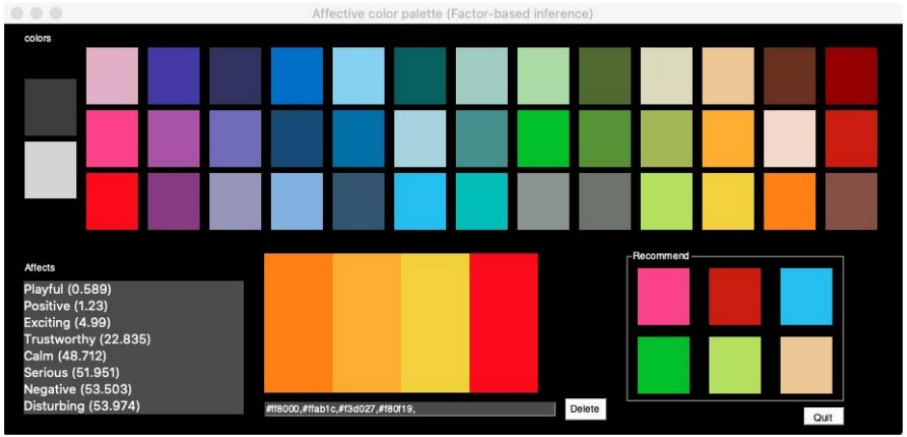
Result

Case III: Predicting colors while inferring the corresponding affective category

Positive



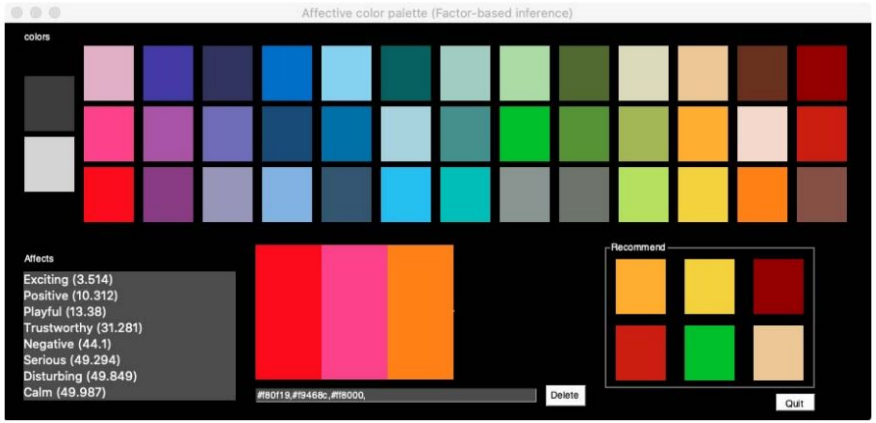
Playful



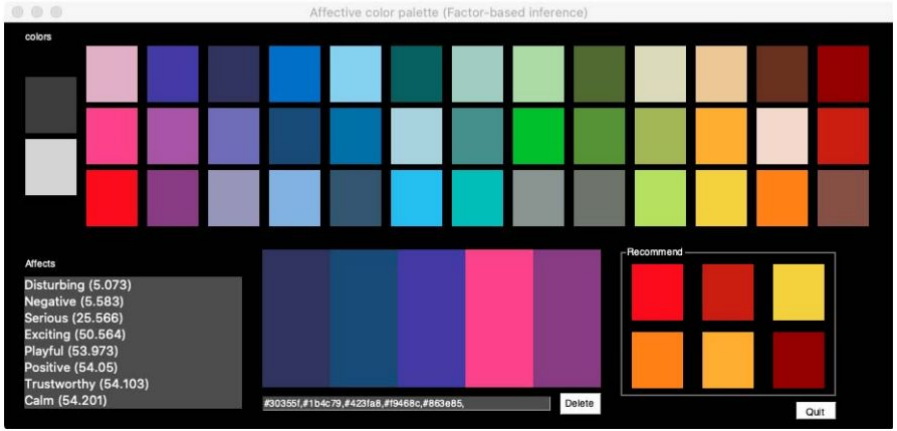
Result

Case III: Predicting colors while inferring the corresponding affective category

Exciting



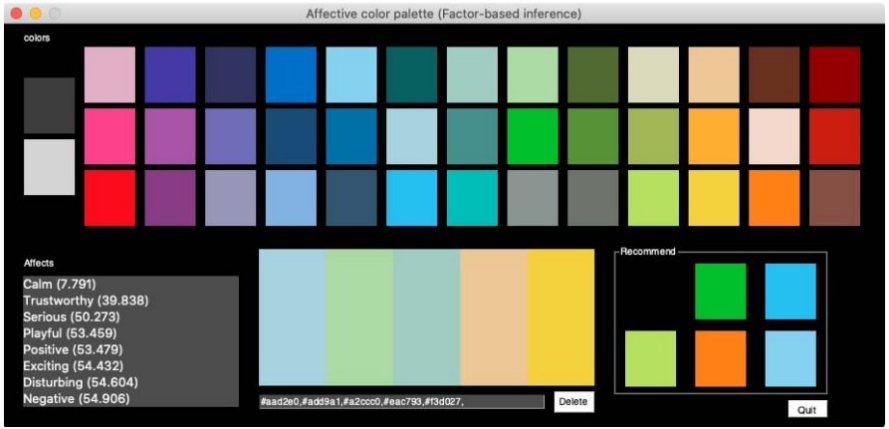
Disturbing



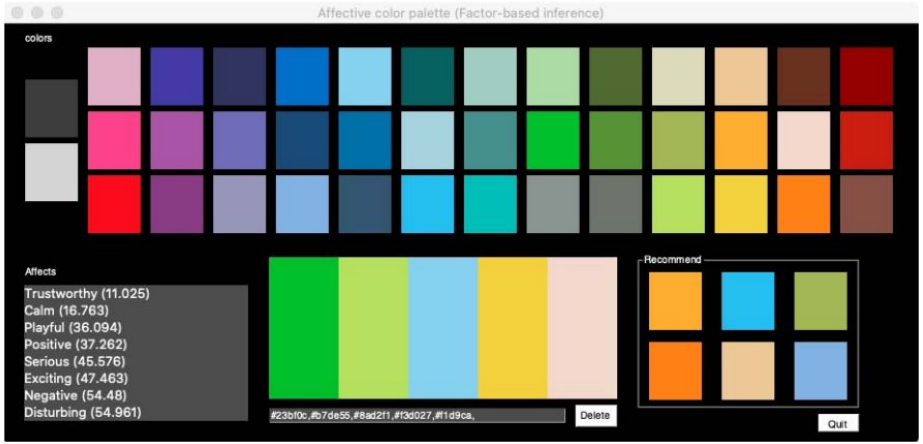
Result

Case III: Predicting colors while inferring the corresponding affective category

Calm



Trustworthy



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Conculsion

- This paper has presented an approach to color palette recommendation that considers emotional expressions and color preferences.

- The three case studies for color palette composition by considering affective types and demonstrated the applicability through interactions with the prototype system.

- Incorporating additional attributes/conditions for recommending colors,develop an interactive tool for adjusting color parameters.

Thank You!