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Developing AI-Powered Virtual Color Consultation Tools for Retail and Professional Customers

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Abstract

The "AI-Powered Virtual Color Consultation Tools" project aims to dazzle professionals and non-experts alike with automatically generated color palettes. Color sets for any kind of design need are achievable in minutes through our easy-to-use system based on state-of-the-art color harmonization rules and AI technology that learns how to effectively combine them. The smart research assistants of this project won't substitute designers and lay users, but instead boost their creativity and efficiency, filtering out unwanted colors and unsaturated configurations.

Colors affect moods and emotions. While colors dominate our visual experience, little attention is normally paid to their combination. Achieving an effective and pleasant color design is notoriously difficult and time-consuming. Yet appropriate and harmonious color combinations can significantly enhance the quality of life of individuals – affecting relaxation in a residence, concentration in a classroom, or thrill in an amusement park, for example. Our thesis is that everybody can act as a designer and organize colors according to his or her personal preference. The color design should merely comply with a user's desire, avoiding the danger of an unpleasant experience caused by random mixing schemes. To achieve that, an automatic retrieval system for personal color design is proposed here. Such a system can offer color design suggestions when powered by additional color rules. Wouldn't it be nice to start or finish well-evaluated color designs in minutes with the help of a personal color palette that would serve a particular purpose and taste?

Keywords: AI-powered Color Tools, Virtual Color Consultation, Automatic Color Palettes, Color Harmonization, Creative Assistance, Personal Color Design, Color Psychology, Mood and Emotion, User-Centered Design, Intelligent Design Tools, Smart Color Suggestions, Personalization, human collaboration, Design Efficiency, Visual Experience, Color Retrieval System, Color Preference, Color Composition, Harmonious Color Combinations, Color-Based User Experience.

1. Introduction

Color consultation is an essential service offered in various industries, including interior design, architecture, fashion design, and painting. Color consultants help their clients to find color palettes that meet their specific preferences and needs. The colors recommended by color consultants can affect how people think and feel, and color consultants use their knowledge of color theory and the psychology of color to help their clients choose color palettes that create the intended effect. Today's color consultants need to work with a wide range of customers, from the most budget-handed, DIY design enthusiasts to those looking for luxury, high-end design solutions. The palettes they create must be tailored to the customer's tastes, routines, and need for brand recognition, as well as fitting into the general context of the building or space and the local environment.

With the emergence of virtual reality technologies, color tools have been developed in which it is possible to see what different colors would look like on a wall or other object. With such tools, a customer can choose their colors without having to use color samples in physical space. Automated online visualizers allow users to play around with colors and color combinations immediately, and some sophisticated visualizers even use machine learning-generated trained datasets of professional color consultants' organizational color palettes to simulate professional color consultation online. Yet the complex combination of the color palette selection process and the experience of color visualization is not yet supported adequately. In this essay, we introduce a tool that combines the methods for assisting in color palette design with the experience of augmented virtuality and reveal its capabilities for popularizing professional color consultation services. We also present case study examples of a design project and color consultancy that have been made possible with our tool.

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Fig 1 : AI-powered marketing

1.1. Core Concepts and Overview

Virtual color consultation helps consumers in need of assistance with color matching. With the increasing number of color-related consumer products, from makeup and hair dye to paints, dozens of companies have appeared over recent years to provide color advice to consumers. Yet, companies rely on trained experts and one-on-one consultation sessions, which are costly and resource-intensive services. Additionally, to fulfill the needs of an increasingly global and digital consumer base, companies are turning to virtual platforms. By leveraging technology, virtual color consultation services can automate consultation processes, streamline business practices, and correspond to online consumer behavior. Virtual color consultation typically uses questionnaires and tools, resources, and visual aids online. Automated suggestions are made for consumers based on recommendations tied to the completion of questionnaires. The goal is to reduce or even eliminate the need for expert involvement and free up human resources.

Advances in artificial intelligence and the availability of compiled consumer data and visual information online have enabled companies to create more sophisticated virtual color consultations. With AI, color consultation tools can automate fundamental aspects of color consultation, such as color fitting, palette generation, and algorithm learning. Subsequently, algorithms optimize for performance using data points and user feedback, advancing the process in a loop-like system. AI analysis aims to adapt virtual consultations to the user in real-time. Workshops on training data, product diversity, and web accessibility are also incorporated into the algorithm-building process. For example, AI takes cues from consumer online interactions, such as pages and products viewed but not purchased, as well as insight from company partners and client brands.

2. Background and Motivation

Color is a notoriously difficult specification that greatly affects the satisfaction experienced with a product, and design professionals and customers frequently engage in consultations about product color during development. Such conversations are often inaccurate and confusing since color experience and evaluations depend on illumination, surface structure, and surrounding colors. In the best case, vast color sample collections are leveraged, and the strategies for defining product color space ranges are sufficient to avoid dissatisfaction with the colors available. In the worst case, a sample may not be available at all, a product's final surface structure is unknown during its specification, or an unexpected surface appearance is revealed in the final product due to inappropriate design solarization. For these reasons, color consultation with digital tools used by design professionals is employed.

Commonly used tools for collaborative product design usually allow discussion, but not accurate joint color matching, selection, or – more importantly – configuration. Specialized color tools typically require both partners to view the same color at the same time. Such advanced physical color consultation devices can be expensive, especially for small non-professional color partners, and remain limited in accuracy and compatibility. Addresses in color space information are generally applied without considering the partner's location in color space or by relying on the transfer of a single color sample. Digital appearance color consultation more accurately supports joint color choices by addressing the partner's unique monitor/surface reflectance combination, but it typically requires specialized software or hardware.

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Equation 1 : Perceptual Color Similarity (ΔE CIEDE2000)

$$\Delta E_{00} = \sqrt{\left(\frac{\Delta L'}{k_L S_L}\right)^2 + \left(\frac{\Delta C'}{k_C S_C}\right)^2 + \left(\frac{\Delta H'}{k_H S_H}\right)^2 + R_T \left(\frac{\Delta C'}{k_C S_C}\right)\left(\frac{\Delta H'}{k_H S_H}\right)}$$

Where

$\Delta L', \Delta C', \Delta H'$: Differences in lightness, chroma, and hue

S_L, S_C, S_H: Weighting functions

k_L, k_C, k_H: Parametric factors (usually 1)

R_T: Rotation term accounting for interaction between chroma and hue

2.1. Rationale for Color Consultation Tools

Why do paint and color product companies invest in virtual color consultation tools? The answer is simple: they want to increase their sales. But for this to be effective, the digital tools need to be as effective as the in-person consultation people love. Research in store formats has shown that in-person consultations yield more satisfaction than just visualizing products on the screen while the opposite often holds when facing the product on the shelf. Satisfaction is crucial as it can affect people's intention to recommend and subsequently the company's brand image.

The dissatisfaction from just visualizing products is intensified for paint and color product companies for two reasons. Firstly, having exterior walls as blank canvases, people have pointed out the difficulty of testing and evaluating colors with physical samples, as the preparation cost of the samples is disproportionate compared to the additional benefit. Color samples are not only heavy and bulky but need to be submitted to multiple exposure conditions such as day and night and always changing natural illumination. Secondly, the ubiquitous but far from universal choice of filters on social media is causing color inaccuracies on a global level, independently of whether or not these platforms were specifically designed to manipulate people's perceptions. Color inaccuracies cause long-standing reputational problems for paint and color product companies and are considered and often dismissed as lacking authenticity. The difficulties in exploring and evaluating colors, combined with the risks of color inaccuracies during physical testing, have encouraged people to shy away from bold color statements, causing them to choose pastel or neutral colors which are usually not representative of their personalities.

3. Literature Review

Color consultation selection in non-digital environments usually happens with industry experience and a physical sample. Consumers provide feedback verbally or by showing physical items in a visual context. In the digital world, applications exist or could be created that allow color matching using different interaction methods that familiarize users with the product quickly. Those would allow communication by the consumer, giving opportunities for feedback and improvement, and showing and pinpointing critical details that need matching. Computerized color matching is not new; certain color-coding systems that map related color zones exist. Algorithms can modify or speed up user customization. They have four steps and user interaction, inputting categories of colors to be matched and then presenting results to be checked. They offer matching of skin tones, hair colors, and eye colors but no samples from the user's environment to be matched. If the user samples the colors with varying conditions and provides them, a mapping algorithm could use them as the control subset instead of having to send the user to the store first.

AI exists in different applications that help retailers. However, they do not connect in-store activities with recommendations for the online store, like an actual integrated experience solution. The internal AI engine behind these solutions uses certain algorithms to work. The AI-based algorithm for matching fabrics is unknown. Different matching approaches exist in fabric matching. Visualization of the algorithm's workings tells how matching happens. Retailers have to predict customer tendencies. If the presented solution combines physical shopping with the online recommendation engine, a smoother and more personalized unified experience could occur. The online recommendation engine could be used more effectively in physical shopping by recommending the user's past selections.

3.1. Existing Color Consultation Tools

Color can cause behavioral and affective responses through associations, memories, and experience which cause individuals to react differently to the same colors. Fittingly, the view of color in architecture and design as a fundamental contributor to experience and well-being affects people's reactions to color. Color also plays a crucial role in product design and marketing: it can communicate essential product attributes or trigger a need. Colors may also be associated with safety, danger, or quality. Colors can steer customers toward desired product associations, such as sustainability and quality; they can also boost brand recognition.

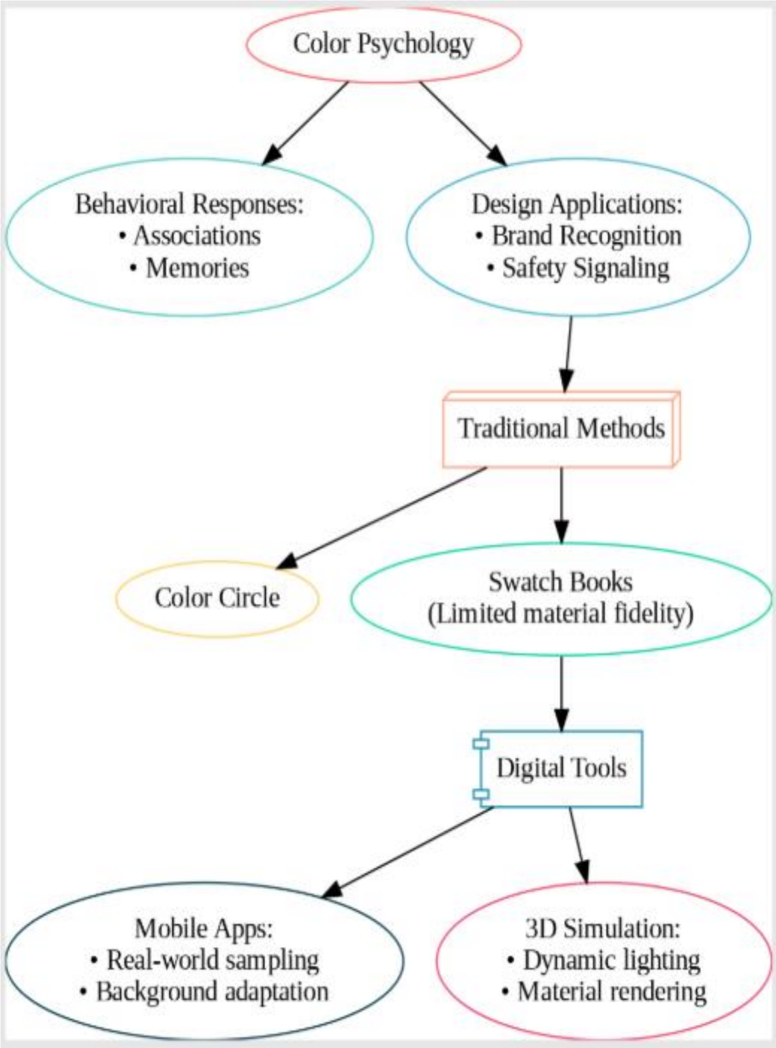

Fig 2 : Color Psychology

In industry, color matching can support both a product and the customer experience. One-to-one matching using a color circle has long been a way for color researchers and professionals to search for and communicate colors. Color matching involves both the selection of a color from an available color palette as well as the transfer to a relevant context such as a facial area. However, color matching requires light conditions, calibration, and a competent professional. A color swatch book helps in visually selecting a color with good apparent color fidelity and precise fate. Standard swatches are limited to discrete reflected colors printed on paper or thin paint film, which means that samples are often either too shiny or too dull compared to the real material. Smartphones and tablets support screened color samples, visible across different backgrounds. Such apps allow the user to select colors in his or her real-world environment and map them to color palette samples.

Corporate developers have produced dedicated apps, mapping users' photos and real-world environments to color swatch palettes. Both approaches help to accelerate the search process for color matching by using photographic or video samples of the relevant application. Users may desire design modifications both during as well as after completion; specific virtual tools simulate color matching by changing colors in a photo. Such photo modifications, however, do not allow dynamic interaction or varying light and material conditions. 3D simulation tools are dedicated to selecting and modifying colors suitable for step-wise visualization and exploration of spaces and interfaces. Such tools use design data imported from production software or made by templates, color palettes, and remapping.

3.2. AI in Retail Applications

The combination of the human-computer interaction field and new artificial intelligence methods develop an ecosystem where retail companies need to redesign and optimize the processes to eliminate the user experience friction points to give the customers what they need when they need it, and how they want it. Along the literature regarding the optimization of critical decision-making processes, we find several examples of incorporating advanced analytics or machine learning methods to help design solutions to prediction, recommendation, and personalization problems. As a way of explanation, it seems obvious that the more complex the more customers, the harder it gets to have these customers redesign the product portfolio decision made by a single brand in the search to keep competing advantage on heading market trends. This complexity has drawn the interest of AI methods like neural networks to learn complex relationships; deep learning to capitalize the processing improvements; natural language processing to infer important signals from huge volumes of qualitative or textual data; computer vision to exploit high dimensional visual data and new marketing decision support systems powered by all of the new possibilities.

Artificial intelligence is already being used to disrupt traditional retail decision support systems. Some companies use machine learning models to define how rapidly prices should fluctuate, how sales should be structured, what should be done with slow-moving items, how delivery prices should fluctuate to increase margin or volume, how the product portfolio should be designed by variants or how the market response of sales and profitability should evolve. Artificial intelligence is already being used also to redefine traditional retail channel management systems. New companies are supporting promotional channel decisions helping firms decide who should get a promotion and which type through databases with thousands of attributes or behavior features enabling the design of prediction models with Bayesian techniques or neural networks. All of these decisions aim to increase market share or sales revenue and profitability margin.

3.3. User Experience in Virtual Tools

Virtual tools create novel experiences for users, but these experiences can be very different from traditional experiences, both physical experiences of traditional systems and virtual experiences with traditional desktop tools. Therefore, designing interactions in virtual systems is a particularly critical issue, which is why it has been strongly investigated by specialists for years. This research teaches how the experience affects the overall satisfaction of the user. When using virtual systems, the agent that is in charge of the interaction plays a strong role in the overall user experience. This role strongly depends on the representation that the system chooses for the interaction. The representation choice influences social perception cues, the configuration of the interaction space, and the consistency of the virtual production, which in turn affects expectations, perception, and evaluation of the interaction.

Moreover, the user experience is not only the interaction with the virtual components but also the effect that the virtual session triggers in the user. It has been found that people using avatars performed significantly better than those who did not use avatars. Users using an avatar experience more positive effects during the interaction and are therefore more willing to return to such experiences. In the domain of color consultations, the degree to which the customer takes the virtual experience seriously influences what the customer gets out of it. As in a consuming experience, the customer needs to feel that the service is dependable, the outcome is positive, and the risk is reduced.

4. Technology Overview

The field of AI bridge methods proposes strategies to assist the user in the exploration of the search space, in the first case using a neural network that generates gradients to optimize the search. While AI is guiding the exploration, the method collaboratively learns from more sketches or wordless descriptions. At every iteration, given the proposed sketch, an objective is evaluated, which can either be: 1) human-assisted evaluation of sketch; 2) a loss model that predicts the aesthetics of an input image; or 3) the cross-entropy loss that marks when some “cheap” options are selected; or 4) a method that compares grayscale sketches over color options. Some of these methods may work better than others depending on the visuals that the data was trained on or how many/what characterization of human assistance was used to guide the learning; future work may follow this exploration. Then, the objective term acquires gradients in latent space using Gradient-based Optimization and a denoising Diffusion Network, while sketch and/or description options are backward in sampling, enabling more space exploration. In this way, the AI-facilitated exploration of the latent space may lessen waiting time as users demand more options. The technique is usable for both traditional colorization and generative tasks. Users are allowed to guide the output further, as seen in traditional colorization methods. Artificial Intelligence Techniques: AI has become indispensable to the art, design, and entertainment sectors; its algorithms have continuously generated logos, animated short videos, 2D illustrations, and photorealistic content. Recent advancements in generative algorithms have made the news, as large companies and small studios turn toward AI in their work. For the digital user experience, combined advances in AI, VR, and AR are turning these realms into hot topics of research. Specifically, AI-powered virtual tools are increasingly supporting the human act of coloring.

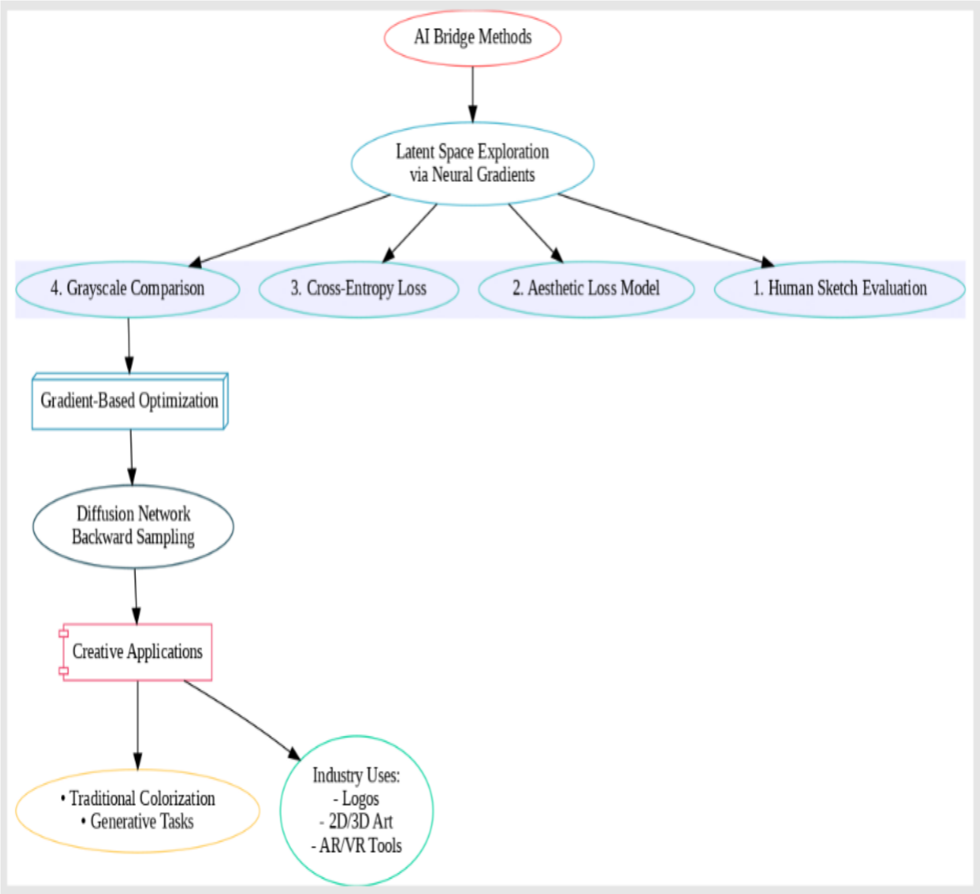

Fig 3 : AI Bridge Methods

4.1. Artificial Intelligence Techniques

The use of Artificial Intelligence (AI) techniques can support the four dimensions of virtual color consultation applications, which consist of: (i) Color and product analysis; (ii) User and context modeling; (iii) Personalization; and (iv) Model validation. First, color and product analysis is required to translate the physical characteristics of colors sampled from real-life items and digital products into the RGB color cube and color spaces. Machine Vision techniques such as color calibration and illumination-invariant feature extraction will be required to this end. Moreover, the product analysis used in most of the existing virtual color consultation tools is restricted to a pre-defined number of color options, which are typically not realistic in practice. AI techniques such as Deep Neural Networks could be used to leverage the potential of generative models to translate a product in a certain color variation into a virtual product.

Second, when using virtual color consultation tools, users may have different rationales, experience levels, and consultation needs; these devices may also be used in different contexts in terms of devices and lighting, among others. User and context models generated either a priori or a posteriori can play an important role in tailoring and optimizing user experience and psychological impact. AI techniques such as supervised and/or unsupervised user modeling, and deep learning-based model compression, could be required to this end. Thus, the goal of personalized Virtual Color Tools is not to replace human expert stylists but rather to include technological support for all consumers. AI techniques can be used on both ends to provide a smart but informal expert-consumer decision process.

4.2. Color Theory Fundamentals

Color theory encompasses a set of concepts that inform how we, as humans, perceive, feel, and think about color. It includes how color components mix and match to create additional colors as well as how those colors interact with one another. The color characteristics described in this section provide an understanding of how color can be utilized in the creation of color combinations that evoke certain emotions or ideas. The basics of paint color mixing, such as primary, secondary, and tertiary colors, and the interactions between the colors on the standard color wheel, are important for understanding color combinations.

The founder of anthroposophy and a variety of art, agricultural, and social philosophies, was one of the first advocates of the use of color combinations based on the emotional aura associated with those colors. He described a color wheel that proposed three categories of colors: Warm colors, Cold colors, and Intermediate colors. Each of these categories had primary, secondary, and tertiary colors within it. More contemporary advocates of color combinations include various authors who describe a variety of color theory combinations, testing, and filters to be considered in developing color strategy and realizing color spaces for design, such as interior design.

Computing a color concept is easy when there are few perceptual color combinations. Deriving a set of perceptual color combinations can be quite tedious. Color combination filters are used to assess how a color looks next to a color concept. If the color concept is too saturated, too competing when put next to a color combination, or has an overly low color harmony, the color is filtered out. Although different colors evoke different emotions in different cultures, rich colors such as deep blues or warm reds against yellows and whites generally communicate a positive feeling in various cultures. Note that the colors involved in the color concept as well as the color combination play a role in why and how events and groups are being communicated.

4.3. Virtual Reality and Augmented Reality

At an abstract level, virtual reality (VR), augmented reality (AR), and the closely related technology of mixed reality (MR) enable the user to see digital content spatially anchored to the physical world. With VR, the user views the computer-generated environment through an HMD, which is often a mobile device. No images from the outside world are visible, thus fully immersing the user in the VR experience. In contrast, AR allows users to see both digital and real content. Digital content is overlaid on top of the view of the real world, thus augmenting the user's experience of reality. In MR, the real and digital worlds interact and influence each other in real time. For example, with earlier versions of MR users could hold a digital object in their hand, but they could still see the real world through real optical see-through displays.
Both VR and AR have been applied in the last three decades to various fields such as industrial design, architecture, and education. They may contribute to a better experience and comprehension because the user can see the changes in the design without leaving their real physical environment. These technologies are seen by some as the future of personal computer interfaces. The introduction of commodity systems such as AR head-mounted displays and consumer VR HMDs has spurred interest in the applications of these technologies in a variety of fields. Other AR platforms include smartphone and tablet augmented, using their cameras to capture the physical world and generate real-time video composited with computer-generated images.

5. Development Methodology

This section describes key elements of the development of the tools in this work and the methods and processes that were employed. We explain how we embraced Agile software development to allow friendly prototypes of color consultation tools to be developed quickly. Having user-centered design as a guiding approach ensured the prototypes were developed under the close guidance of end-users.

1. Agile Development Process

The AI-Powered Virtual Color Consultation Tools themselves consisted of three prototypes developed in a wizard-style fashion. One of the wizard implementation paths included one major version with both the backend and front-end being developed together and two subsequent minor versions that included the front-end updated based on end-user feedback. The wizard-style implementation on the prototypes was split into three major parts those being the back-end modules, the front-end website used to query user input, and the color palette generator design to cohesively generate an output based on the data returned from both the front-end interface and back-end color analysis modules.

The tools were developed iteratively, guided at each iteration by input from a group of suggested end-users via phone, email, and user testing sessions that employed think-aloud protocols. This embrace of an agile approach was made easier by the low-cost technical capabilities provided by cloud computing and a large component library of pre-existing software modules that provided modular capabilities and functionalities. Our tools rely heavily on a broad set of pre-developed modules and software libraries for computational tasks like user interface, data handling and storage, and machine-learning-based image processing and semantic segmentation. This modular approach made it easy to develop, incrementally integrate, and modularly maintain different components of the larger system.

5.1. Agile Development Process

Introduction and Motivation

During 2020-2022, we developed a Virtual Color Consultation Tool to support the presale of paint and color products. In this process, several questions related to the development process arose, such as: Should a tool that serves an expert, professional in consultation with years of experience, be evaluated and tested? Should it follow usability design steps? Would that be superfluous? Would a usual design process involving designers and long explanations of interaction semantics be good for developing a consultation tool for non-experts? A tool in the style of Wizard of Oz, adjusted by experts, the designers, and developers of the tool, only using their background knowledge and expertise? Would an agile

development process where the tool is evaluated with real users, the clients, and their end customers, provide better results?
This research paper describes the development process of this tool and all the warm and cold moments we encountered on the way. Experiences shown here involve proper solutions, sides to be improved if a new iteration is done, and how agile design combined with user-centered design principles showed the best results in each of the stages of the project.

An Agile Development Process
To develop the tool, we opted for an agile development process, specifically Scrum methodology, since at the project’s beginning phases, there was a lot of uncertainty about colors and shape combinations; it allowed us to obtain user feedback as fast and as often as possible. The project consisted of short phases of about four weeks: at the end of each phase, a new version was presented to the end users: and consultants involved in color decision processes related to architecture, interior design, or audiovisual industries. In addition to formal meetings, version operation testing, and continuous chats regarding doubts and proposed changes, we also had scheduled daily stand-up meetings. Some end users met at our labs during the local design phase, and others used their computers from home during the lockdown to another location. We did not want to lose empathy, collaboration, share ideas, and work on soft issues among all participants. Daily meetings made this goal possible, thus avoiding using formal chargeable tools.

Equation 2 : Personalized Color Match Score

$$M_s = \omega_1 \cdot S_c + \omega_2 \cdot P_u + \omega_3 \cdot C_e$$

Where

M_s: Match Score

S_c: Color Similarity Score (e.g., ΔE^{-1})

P_u: User Preference Weight

C_e: Environmental Context Encoding

$\omega_1, \omega_2, \omega_3$: Tunable Weights

5.2. User-Centered Design Principles

The UI design of color consultation systems has been mostly informal, driven by designers' formal design education and their experience with color in printed or screen displays, but non-verbal enhancements have often violated basic design principles associated with virtual environments for gerontological and handicapped users—the target clients for vendor-consultant projects. A major objective of our study has been to formalize data-driven design principles for these systems. We approached this goal by an equally-data-driven approach to user interface (UI) color assignment and then woven those decisions into recommendations for color assignment in general. Further, the study of color influence from a more practical and less theoretical stance applied design decisions to commercial color-matching products. Model combinations were matched to the color appearance of actual prints and used to create a color appearance file translated into a color appearance module.
In our work, the user understands and specifies the intended use cases for the color assignment to be accomplished. Even when developing assignments for very generalized color intent categories, like those for the skin or travel cases, the template forms associate a color assignment to a color use via colors being used for objects having strongly implied uses from the current Color Group. Pioneering work in the area of applying principles to color assignment has also been done on a more UI/UX general basis. We extend this work as it pertains specifically to the use of color within interactive computer graphics applications. Other work has also been done on UI-based hue color wheels and interface allocation tables for real-time physical application color assignment from model values.

6. System Architecture

The overall architecture of our Color Consultation Tool is described in this section, which is centered on the integration of dedicated AI Models focusing on color analysis. The latter can analyze input images either by detecting the body region in the image or by applying clustering models on the color detected on the input image. About the system architecture, we mainly focused on web-based architecture. User interaction is enabled by a web app developed using JS Framework for Frontend and JS Framework for Backend. We integrated two AI Models at the backend using framework and API, making it interoperable. The input is the image uploaded (preferably a portrait) by the user and the output is the color palette suggesting colors/frames suitable for the user. Users are also able to adapt and change model parameters to further tune the prediction process.

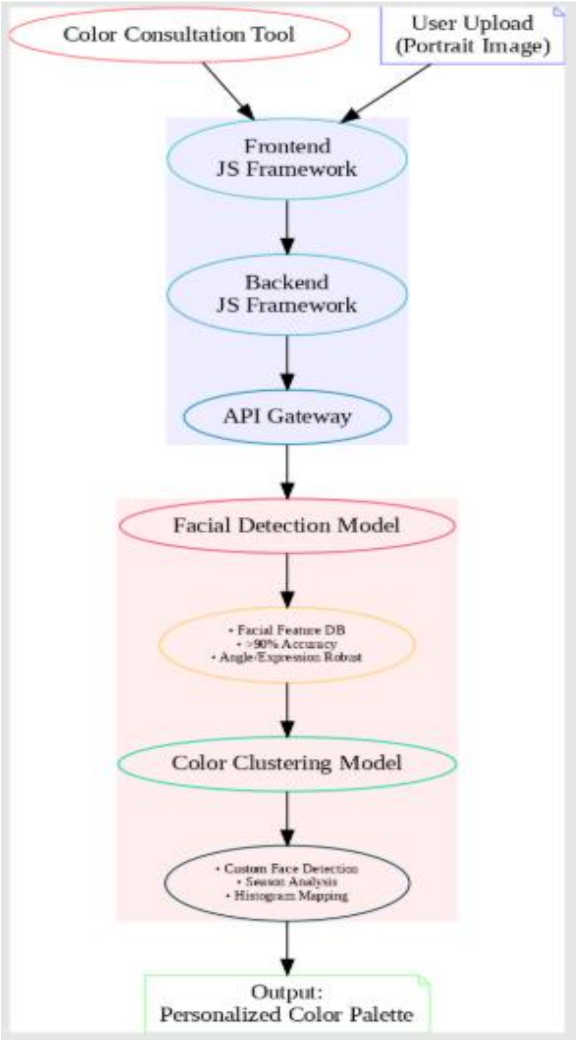

Fig 4 : Color Consultation Tool

The first Model is a Databased Detection Facial Model developed with the help of using a based Model. A collection of images from the Facial Feature Database containing different faces are collected and classified based on the Hair Clustering Colors generated by the Clustering Algorithm. Upon testing, we achieved more than testing accuracy in detecting the facial region in portraits at various angles, facial expressions, and dark backgrounds embedded in the images. We optimized the model to make it responsive on for-for-instance faces. The second AI Model is the Color Clustering Phase, which is a bleeding-edge AI Application for Automatically Suggesting Colors for Outfits Using the Clustering Method. It is mostly driven by script(s) using a Library, Clustering algorithms, and the Season Analysis Formula. It employs Custom Face Detection to detect the Region of Interest Estimate Required Color Histograms Map colors palette and files the Output suggesting top colors the User Should Use.

6.1. Frontend Development

In recent years, color selection tools have gained rising interest in a variety of different fields. We see research in paper art, augmented and virtual reality, and even room design who are utilizing color selection in new interactive ways for the user. However, user interfaces are usually limited to some preset color palettes that confine the user's creativity. Aiming to broaden the creative potential of these tools, a vast number of different frontend development toolkits have been developed that enable users to set up their parametric rendering algorithms and display these on interactive desktop user interfaces.

Based on WebGL embedded-in-browser, our tool utilizes a custom shader that implements a composition of complex scripts. The development of the frontend tool was primarily done in JavaScript. Therefore, interfacing and connecting the shader to HTML controls can be performed by any front-end developer. Moreover, we combined our shader with a set of further customizing features to the Generic Shader Creator, an easy and flexible Managing Editor that lets users customize any features of a paper and export it to a PDF. Based on the easy management of small and mid-sized generative solutions in a web environment, we hope to make generative design available for a wider range of users.

6.2. Backend Development

Overall, the backend development of our project included the following major steps: 1. setting up a server, 2. implementing a data preprocessing pipeline for user input images, 3. integrating APIs for language modeling and color palette extraction, 4. implementing APIs for color palette visualizations, color suggestions for user input images, and 5. aggregating the above APIs into a four-function app, using Flask.

Figure 2 illustrates the overall structure of our backend component. A virtual machine virtualizes a Linux OS environment that runs Flask Backend APIs integrated there, as illustrated in the APIs section. After that, Flask APIs implemented several data processing instructions, as specified in the previous paragraph, once the user input data was completed.

We decided to build the project backend using Flask, given that it is a very lightweight framework compared to Django, taking into consideration our underlying use case of designing just a few Backend APIs to serve the frontend requirements. Flask is also based on Python and can run various core Python libraries that help us to do data-preprocessing tasks, which is our main job of implementing the asynchronous Backend APIs serving the Frontend requirement. Compared to Django, Flask also has an easier setup process than Django, and designing APIs is more convenient. Lastly, the simpler project structure of Flask makes it easier to code, understand, and maintain. Those reasons made our choice of framework easy.

6.3. Integration of AI Models

Before going into model integration, we first introduce three models: GPT-3, Fawkes' Cross-Modal Contrastive Learning Model, and ATLAS Model. To integrate the three AI models, we developed a REST API on the backend. The front end for both virtual consultation submissions and feedback submissions was built on Next.js, using Material UI for the component library. The project structure employed serverless functions for the REST API routes, Typescript, and Redux for client-side state management and asset storage. For the front end, we used system prompts to initialize each model and any context for the specific query. For the backend, we used the three models for inference and submissions to the models. For GPT-3, we used the completion method. For ATLAS, we used the method for image captioning. For Fawkes, we used inference for existing target images and all queries for new target images. For both the front end and back end, we took relevant additional precautions to limit model failure.

GPT-3 Text-Completion Model has established pipeline-first pre-trained language algorithms that are general enough to perform as benchmarks for downstream tasks with few examples, such as dialogue generation and summarization. The "Mistral" is an improved Relax-and-Relaxtien variant of a pre-trained transformer based on the decoder using eight and a half billion parameters better than GPT-3. For our architecture, we selected three methods for integrations: Conversations as Code generation / Templates as Completion. We also used System Message Design and provided available messages for conversation initialization. In our use case, the expert virtual consultants submit the color scheme to model inputs.

7. User Interface Design

Designing the user interface for a virtual color consultation tool is a unique and challenging task. Users want to be free to explore thousands of colors and color combinations, but at the same time, as novices to color decoration, they often need guidance to help them choose colors that will produce attractive results. In a live consultation, an expert balances these two aspects; a virtual color consultation tool should aim for a similar balance. A well-designed interface can help novices overcome their lack of experience and enticement to explore thousands of options can lead to a richer experience than a single expert-consultant session. In this section, we discuss design considerations and describe our prototyping and testing process.

Design Principles for Color Consultation Color selection interfaces used in color consultation tools span a range of designs, from beginners' traditional paint chip pizza to commercial paint company's virtual tools to complex graphics created using design software. From our research on the commercial tools currently on the market, it appears that novice users most often employ a color selection scheme with either a predetermined set of colors, a photographic background, or both. Our recommendations for a virtual color consultation tool's design are influenced by the Action Science and collaborative learning approaches of design research. Our recommendations are based on two sources of insight: one from knowledge of the design principles employed in commercial tools available, and a second from an understanding of what novice users value in virtual color consultation tools designed for novices.

7.1. Design Principles for Color Consultation

The design principles we outlined for color consultation require us to consider the cultural context of participants involved in virtual color consultation. First, color consultation is a two-way conversation between a consultant and a client, and for most clients, it is an exciting but stressful experience. A consultant has more than the expert's role; they also guide, direct,

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and interactively modify a client's opinion and emotion about colors to help them tackle a design problem. Therefore, a color consultation tool must support both sides of discussions and maximize the joint engagement from both sides.
Second, a color consultation is highly personalized. A client's previous color choices and design preconditions greatly impact their color preferences. A consultant must track the client's color interests throughout the stages of the consultation before generating the best recommendation tailored to their personality. Therefore, a color consultation tool must remember a client's previous input. This would be simple if a tool is only server-based. However, generating a recommendation requires a tool to transfer the client's input color preferences back and forth between the client and the consultant. Delay or low throughput may significantly disrupt the consultation flow, limiting the level of interactivity and engagement.
Third, a color consultation focuses on specific spaces and applied functions. These application areas often affect the perception of color for both sides of the consultation: clients are likely to have different aspirations for what works and what does not for specific spaces/functions, and consultants have their own experiences and knowledge during the consultation. During a hybrid consultation, a color consultation tool must enhance the ability of color preference consultation for specific spaces or functions throughout the conversation.

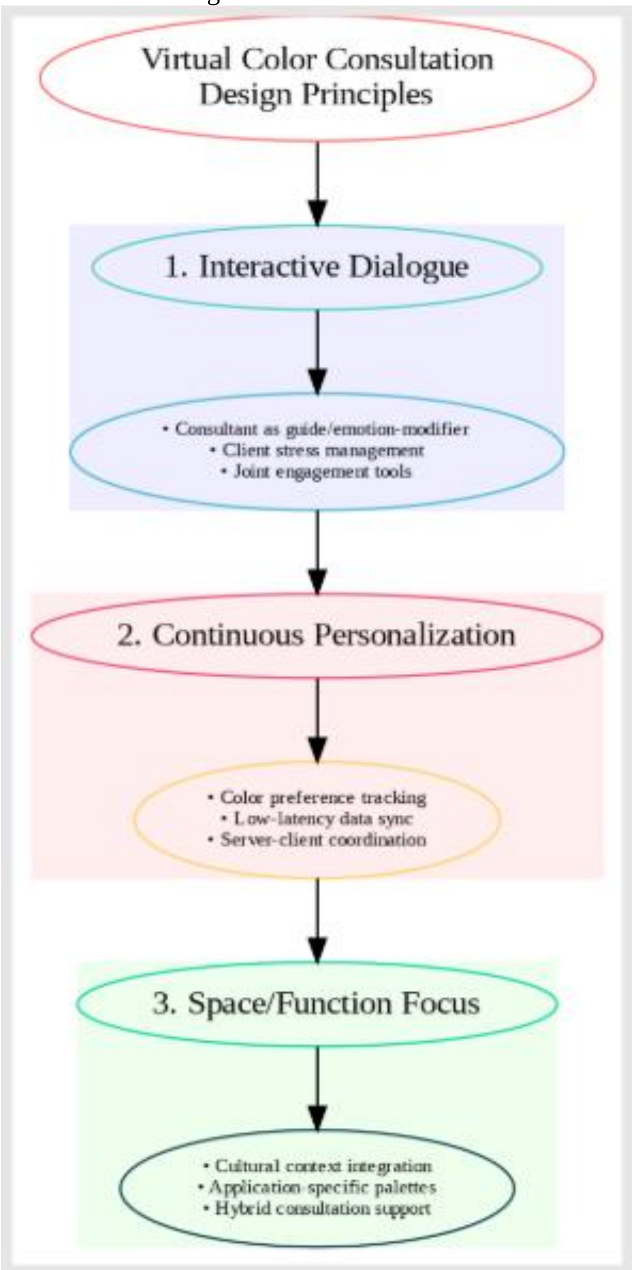

Fig 5 : Virtual Color Consultation\nDesign Principles

7.2. Prototyping and User Testing

We constructed four color consultation prototypes that embodied choices we made based on the principles. We derived prototypes from multiple applications of color consultation, including textile design, editing photography for color-monochromatic color palettes, and using palettes to instruct the application of a given color palette to a third party's object. Prototypes included Lighting Palette that combined color-matching software and digital camera hardware for capturing natural outdoor and indoor light palettes; Light Palette for wire-frame modeling of observing complex 3D objects in planar layouts with embedded light-matching functions; Monochromatic-Color Palette; and Color-Shaper Palette.

User testing and feedback led to more questions than conclusions about user joys/dislikes of palettes. Participants experienced high user frustration with the learning phase when use required careful technical dexterity with a new device. Self-discovery of features and functions stimulated awe and wonder but was overly complicated by most available educational tools. Participants enjoyed using color palettes but were still end-user-targeted explorers at the end of the testing session. Concepts like these, about the user experience dimensions, are key to Usability Engineering.

The shape and color consultation functions of prototypes found usability issues, wands-demanding exploratory interaction that spurred awe and wonder but were also overly complicated by problems with gaining reliable user dexterity control; and lag-inducing calibration image acquisition and stereotype-breaking unexpected behavior. Results suggested prototypes could be valuable training and practice tools for professional artists, designers, architects, photographers, and students working in related fields to richly explore shape/color design possibilities.

8. Data Collection and Management

A supportive, flexible data collection and management approach is required to enable color consultation using AI. Not only does a color consultant need access to a color choice database, but data-driven decision-making increasingly relies on other databases such as sales and customer inventory databases that are separate from the color choice database.

In some instances of applied AI work, the data available may not be core to an algorithmic model that is created. This situation may occur when an effective algorithmic model prediction is developed that can be used for a product or service, and the company's brand and proprietary market knowledge is used instead of its data to drive the business anyway. Artificial intelligence work may also rely on data assets being separate from analytic models with the associated ownership and copyright defined. Intelligence model development may not rely only on one industry-specific decision-making aspect. Some existing aesthetic promotion models rely only on architectural features, while others account for different aspects.

When training a color consultant AI tool, the following types of data can provide a robust foundation: A dataset that consists of colors that other people prefer to use when selecting color themes in the topic domain is important. Such data can be gathered by reviewing images and subsequent color extraction from the images. Such extraction must be controlled for image quality and relevance to the topic domain, as image quality and color relevance affect perceptions of color harmony or discordance.

8.1. Data Sources for Color Analysis

The variety of data sources containing color information is significant. Users upload and share their work for different services, such as photography, digital art, and others. Within this platform, the available datasets provide a varying amount and quality of color proposals. Color proposals may contain a large number of color palettes created by users from photos and designs uploaded within this social network, providing possibly interesting color combinations with a specific purpose. A relatively new color inspiration website provides a simple interface to find color palettes created from images uploaded by users. Each palette provides information like the prominent colors in the proposal and the image it was created from. Users can also use the board feature to save their favorite palettes. Another color inspiration website contains a database of palettes created from colors uploaded by the users. Each palette has attached a board section that allows the user to group palettes they want to save and return to choose from them.

Another data source that can be used is color dictionaries. These are usually collections of named colors curated from several sources that aim to catalog and name colors, as well as their meaning, properties, and origin. Some color dictionaries were created based on the web, improving their reach and accuracy. Different dictionaries can use different RGB representations of the same color, but some are implemented in services with converters. These services use ten colors, the ten transitions, and then use interpolation to provide RGB estimations according to the chosen RGB representation of the color. These are useful not only for finding named colors but also for naming specific colors, using their RGB representation. Alternative services were developed to provide easy access to specific databases, either to share colors, create color collections, or even allow the user to name or get the name of a color by selecting its RGB values.

8.2. Privacy and Ethics in Data Usage

A growing number of AI applications that leverage face data are surfacing, requiring us to start seriously think about some privacy and ethical issues surrounding the data privacy consent. These products make use of face images to train AI algorithms for a diversity of services including real-time face alignment tracking, representation, makeup transfer, style reference, appearance alterations, facial recognition, avatar creation, among others.

However, almost all such methods for face visual manipulation rely on facial datasets collected from various sources and do not concern themselves with the methods of collecting those images, nor consider whether the original creators of the public images were aware that their data would be used for such purposes, nor the fact that a majority of those images had not been specifically consented by those individuals. As the computer vision community inches towards the creation of products that will directly be available to the world's general public thanks to new face manipulation generation systems, appropriate policies regarding data usage and user privacy must be followed to avoid backlash similar to that faced by several other industries.

But what does that mean in practice? For starters, the field must harmonize methods for testing and benchmarking across different datasets to avoid inventing new datasets whenever a new task is introduced. In addition to clearly specifying and understanding the implications of how datasets are curated, it is crucial to guarantee that datasets are sufficiently large and diverse. Our face images change across time and space for a variety of factors such as aging and environmental factors, and products such as those dealing with real-time appearance transfers should mirror this by training with the most representative datasets.

9. AI Model Development

In the base prototype, a simple pipeline was implemented based on clustering onto one defined color space. To improve the accuracy of the proposed solution, a more advanced model was developed. In the general color-matching task, the goal is to predict the most accurate answer (the color of interest) on the predefined values of the input space (the features). For this purpose, supervised learning based on classification and regression tasks can be defined. In the case of color selection, supervised training is defined as a classification task, whereas the color analyzer–color matcher task, is defined as a regression task. In the proposed model, both methods will be used. A color matcher is part of the proposed color consultation pipeline. The model operates as a prediction answer of the coloring methods in the cases of manual color selection and color matching. The scope of artificial neural networks is about the included scopes of simple classifier and regressor models. For the color matcher task, the required features, such as color harmonization, FFE texturing, and the selected regions on the object, are applied.

Training Data Preparation

The first model is designed as a simple color classifier, which assigns a collection of the basic colors to the input color. There are 27 basic colors selected from different color palettes. Sampled colors are selected from the K-means clustering method, based on the input color. Additionally, both unique and repeated colors are recorded, and the models are trained by both datasets.

Additionally, two other parts of the pipeline are required. The first one is the texture NV; this is a normal vector calculated in the color analyzer function. The second one defines the input RGB data requested by the RNN color matcher apprentice, which is referred to as classifier CNN. The texture is generated for all colors repeated in the database; afterward, they are filled in the output empty RGB shape for the color matcher.

9.1. Training Data Preparation

In this section, we discuss how we sourced and prepared a dataset to train the AI models underpinning virtual color consultation tools. Using the datasets, we trained AI models to predict the suitability of hair and skin colors and undertones for a large number of hair color shades. In doing so, we addressed unique data challenges compared to traditional AI tasks of object detection and image classification.

We required personalized datasets linking hair and skin color information for many individuals to color hair dye shade suitability. Color selection at a beauty store is typically done using artificial mannequin heads. While it is prudent to examine hair colors on an actual person, the available datasets did not fit our requirements. Therefore, we decided to create a dataset from social media images that feature makeup artists and their customers. We explored publicly available datasets and classified their suitability for our task. Based on our findings, we found that the most suitable datasets are those that use real photos that display individuals wearing dye shades. So, we decided to use these two datasets that meet our requirements. Other publicly available datasets do not include dye hair color.

HAIR is how we will refer to the combined datasets. The HAIR dataset contains a total of 1,389 images of 853 unique persons, with people of different ages, hair colors, races, and diverse ethnic backgrounds. All color annotations were verified by a professional colorist. The HAIR dataset is unique since it contains color annotations of hair dye shades suitable for individuals spanning different ethnicities and ages. It is the only dataset that was created for that particular problem.

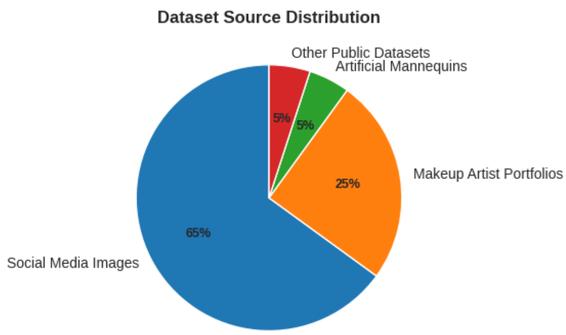

Fig 6 : Dataset Source Distribution

9.2. Model Selection and Evaluation

In Section 2, we discuss how to select the most suitable model from a large pool that includes both standard computer vision and state-of-the-art generative deep learning models. To do this, we divide our available data, containing 104,603 images, into a small evaluation set with 92 images and a training set that contains the rest. We then use various pre-trained standard computer vision models that cover a range of architectures: VGG16, ResNet50, InceptionV3, EfficientNetB0, DenseNet121, and MobileNetV2 that are all trained on the dataset and five transformer-based models, Vision Transformer, Swin Transformer, DeiT, CrossViT, and T2T-ViT. All of these use the same data augmentation processes and are trained using the Adam optimizer with a learning rate of 1e-4 and an early stopping criterion based on the validation accuracy. We employ the same training strategy on generators of StyleGAN2-ADA, AnyFace, and GANPaint Studio as well.

The choice of the number of evaluation images is based on the need to eliminate the noisy predictions caused by model weight updates during the training phase. Hence, we have chosen a set of images that contributes a negligible estimation error. To evaluate the models, we calculate their prediction fidelity in terms of the agreement index between the predictions of these models and ours. Our results show that all pre-trained vision transformer-based models perform remarkably well for all prediction categories, while in second place are the MobileNetV2 and EfficientNetB0 standards computer vision models with their data-agnostic predictions. They are followed by the InceptionV3 ResNet50, and DenseNet121 VGG16 models while in the last place are the pre-trained GANPaint Studio and StyleGAN2 generators.

Equation 3 : Neural Network-Based Color Prediction

$$\hat{Y} = f(X_{img}, X_{pref}, X_{env}; \theta)$$

Where

$\hat{Y}$: Predicted Color Suggestion

X_{img}: Image Features (room, object, etc.)

X_{pref}: User Preferences

X_{env}: Environmental Conditions (lighting, space)

θ: Model Parameters

10. Conclusion

A great challenge facing color professionals today consists of providing color consultation services at a scale to service the needs of diverse consumers across multiple markets. Moreover, many consumers find the existing access models for color consultancy to be severely restrictive and inaccessible. While color professionals are required to process at least three years in color theory to obtain color qualifications, advances in AI have enabled us to build systems that can simplify the knowledge transition from experts to end-users. This field of research opens up many interesting implications for AI-charged Industry 5.0. Notably, the AI consultant would serve as a trusted advisor while end-users, also termed as consumers, become actively involved in the decision-making process and benefit from the symbiotic relationship. We proposed the use of AI-powered virtual Color Consultation Tools to ease decision-making in the process of color matching.

The process requires integrating AI-Supported Color Visions with Web-Based Direct-To-Consumer Platforms. Professional consultation services should gradually shift their focus from traditional B2B services to embrace DTC product-oriented industries powered by consumers. By enabling a two-way flow of knowledge between color professionals and end-user consumers to aid the color decision process, both parties can gain benefits by democratizing color wisdom and harnessing the advantages of collaboration support tools distinguishing the Technology-Push vs. Market-Pull Strategies. This process can also encourage consumers to participate in social scoring with the ultimate aim of creating color masterpieces merging artistry and commerciality. Using technology to foster more connection between designers and consumers, while still leaving the creative power in the hands of individuals.

10.1. Final Insights and Future Directions

AI-Powered Virtual Color Consultation Tools Conclusion and Future Directions Like many other tasks that require expert knowledge and innate skill, color consultation is increasingly becoming automated and made available to those without experience or training. Though assistance by an expert can help address aspects of customer satisfaction and make a consumer's color choices well-informed, it can be limited by the customers' geographical availability and time restrictions. Virtual color consulting tools offer an alternative pathway that uses computational techniques to provide personalized assistance to consumers. In particular, this work has highlighted a selection of AI-powered systems that use novel design methods to help create desirable color combinations. Though much progress has been made, there still lies much more to be desired from these systems. These systems provide a wealth of product and user datasets associated with the colors they generate. By leveraging such datasets, future research may develop their models to be more robust to compute and enhance the level of acceptance of the recommended color choices.
Novel perceptual color spaces and functions optimized for evaluating results that satisfy both aesthetic and functional constraints are required to make significant strides in the field of color combination design. These tools could aid non-expert users in designing products with color palettes that balance overall aesthetics and harmony with functional performance. Such tools could also offer suggestions to experts needing to examine an abundance of facets before finalizing their palette choices. Instead of completely automating, we could look towards AI systems that assist expert designers in accelerating their color selection, inspection, and application tasks. Such tools could substantially reduce the design time and cost with the assistance of non-experts without reducing any of the expertise or experience needed to finalize major design decisions.

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