Data Driven UI Colour Selection for Enhanced User Engagement

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ABSTRACT

This study highlights the importance of color selection in user interface design, as it can influence users' perceptions, emotional responses, and levels of engagement. Many applications still rely on designers' intuition without strong empirical evidence. **The objective** of this research is to develop a data-driven framework for User Interface color selection that can measurably enhance user engagement and satisfaction. **The method** involves collecting a large dataset of color schemes from various popular applications, followed by preprocessing steps such as normalization, clustering, and analysis of the relationships between colors and emotional responses. In addition, user interaction metrics and engagement data are analyzed to evaluate the impact of specific color combinations. **The results** show that certain color palettes consistently generate higher levels of engagement, with specific hues and contrast levels improving users' attention and effectiveness in completing tasks. The analysis also identifies patterns that can serve as guidelines for designers in selecting colors that balance aesthetic appeal and functional performance. **The conclusion** of this study is that adopting a data-driven approach to User Interface color selection leads to a significant improvement in user engagement, while also providing practical guidance for designers and developers to optimize digital interface experiences.

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1. INTRODUCTION

Color selection is a crucial aspect of User Interface (UI) design because color plays a significant role in shaping visual experiences and user interactions. Numerous studies have shown that color can influence perception, evoke emotional responses, and even guide user behavior when interacting with applications or websites [1, 2]. For example, certain colors can increase attention, create a sense of urgency, or strengthen brand identity. However, despite its substantial impact, color selection decisions in design practice are often subjective and rely heavily on designers' preferences or intuition [3]. This condition poses a challenge, as not all color choices are able to produce optimal levels of user engagement [4]. Therefore, a more structured and data-driven approach is needed to ensure that color design decisions deliver effective and consistent results in enhancing user engagement.

Although color strongly influences user perception and behavior, User Interface color selection still largely relies on designers' subjective judgment, which does not always lead to measurable improvements in user engagement [5]. Currently, there is no clear data-driven framework that systematically links User Interface color characteristics with engagement metrics [6]. This limitation becomes more critical in blockchain and decentralized applications, such as DeFi platforms and digital identity systems, where interface clarity and visual trust cues directly affect user confidence and interaction [7]. Inappropriate color choices can increase cognitive load and reduce usability, highlighting the need for a data-driven User Interface color selection approach that provides objective recommendations and strengthens transparency, trust, and engagement [8]. Therefore, this study proposes a predictive model that recommends UI colors based on user interaction patterns and measurable performance metrics, particularly for decentralized platforms such as dApps, cryptocurrency wallets, token exchanges, and blockchain dashboards, where clear visual indicators are essential for communicating transaction status and security information [9, 10, 11].

To clarify the direction and focus of this study, the research objectives are formulated in a hierarchical structure that illustrates the relationship between the primary goal and its supporting objectives [12, 13]. Visualization is required so that the interconnections among the objectives can be understood systematically and easily interpreted. Therefore, this study presents Figure 1. Research Objective Pyramid as a conceptual representation that illustrates how the research objectives are arranged in stages to achieve improved user engagement through a data-driven approach to UI color selection.

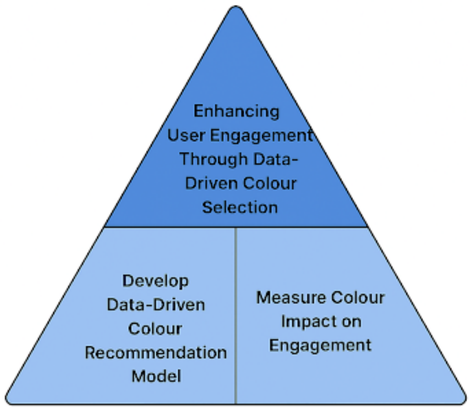

Figure 1. Research Objective Pyramid

Based on the visualization in Figure 1 Research Objective Pyramid, it can be understood that the primary objective of this study is positioned at the top of the pyramid, which is to enhance user engagement through data driven UI color selection, supported by two main goals at the lower level, namely the development of a data driven color recommendation model and the measurement of the impact of color on user engagement metrics, indicating that achieving the primary objective strongly depends on the successful accomplishment of these supporting goals thus, the Research Objective Pyramid emphasizes an integrated research approach that combines analytical model development with empirical evaluation, enabling UI color selection to be carried out objectively and based on evidence, and to achieve the formulated research objectives, it is necessary to define research questions that specifically guide the analysis and evaluation process, since research questions serve as the main foundation for determining the methods, data collection, and analytical techniques employed in this study, therefore, this research focuses on identifying the colors or color characteristics that are most effective in enhancing user engagement and understanding how user interaction data can be utilized as a basis for decision-making in UI color selection, and by addressing these questions, this study is expected to provide deeper insights into the relationship between UI color and user engagement while supporting the application of a data-driven approach in the interface design process [14].

This study makes three main contributions. First, it develops a data-driven predictive model to objectively analyze the relationship between UI color characteristics and user engagement [15]. Second, it constructs an engagement color dataset that integrates visual color features with user interaction data to support further research. Third, it proposes an implementation framework that allows the model to be directly applied in UI design workflows across digital sectors such as e-commerce, blockchain systems, and mobile applications [16, 17]. In line with the United Nations Sustainable Development Goals, particularly SDGs 9, this approach promotes innovative and sustainable digital infrastructure by integrating user interaction analytics into UI color design [18]. It is particularly relevant for blockchain and distributed ledger technologies, where clear and trustworthy interfaces are essential for adoption [19, 20]. Optimized contrast, semantic color mapping, and visual hierarchy can improve transparency, usability, and trust in systems such as DeFi platforms, cryptocurrency wallets, and smart contract dashboards [21]. Furthermore, data-driven UI design can enhance visualization of transaction processes and system feedback in blockchain environments [22], while also supporting Sustainable Development Goals (SDGs) 8, SDGs 4, and SDGs 12 by improving digital productivity, learning engagement, and more efficient digital product development [23].

2. LITERATURE REVIEW

2.1. Colour Theory in UI/UX

Color theory is an essential aspect of user interface (UI/UX) design because color functions not only as an aesthetic element but also as a visual communication tool that influences user perception and interaction [24]. In UI design, color helps establish visual hierarchy, distinguish interface components, and improve readability and visual comfort. The Hue, Saturation, and Brightness (HSB) model is commonly used to describe color characteristics, where hue represents the base color, saturation indicates color intensity, and brightness determines lightness and element visibility [25]. In addition, principles such as color harmony and contrast are important for maintaining visual balance and ensuring clear distinctions between elements like text and background, thereby improving accessibility. From a psychological perspective, color can influence emotions, attention, and decision-making, affecting how users interact with digital systems [26]. Therefore, understanding color theory and behavioral psychology provides a strong foundation for designing interfaces that are visually effective and capable of enhancing user engagement [27].

2.2. User Engagement Metrics

User engagement is a primary indicator for assessing the effectiveness of user interface design, as it reflects the level of user involvement in interacting with a system. Engagement is measured using quantitative metrics that objectively describe users' responses to UI elements.

Click-Through Rate (CTR) measures the percentage of users who click on a specific element relative to the number of impressions and is therefore commonly used to evaluate the effectiveness of visual elements such as buttons or calls to action [28]. Time on task measures the duration users spend completing a task or using a particular feature, reflecting both engagement and interface efficiency. Interaction rate indicates the frequency of user actions, such as clicks or scrolling, which illustrates how actively users interact with the system. Meanwhile, bounce rate measures the percentage of users who leave a page or application after minimal interaction, which generally indicates low engagement.

2.3. Data-Driven Design

Data-driven design is a UI approach that replaces subjective assumptions with user behavior analytics to objectively evaluate visual elements, including color, through measurable engagement metrics. Supported by machine learning techniques such as regression, classification, and ensemble learning, this approach can model complex interaction patterns, predict user responses, and generate adaptive color recommendations [29]. In blockchain ecosystems, it can be integrated into decentralized dashboards and smart contract interfaces to improve clarity, transparency, and user trust. Although prior studies show that data-based color selection enhances engagement compared to intuition-driven methods, most remain limited to controlled experiments or heuristic rules [30]. Recent interdisciplinary research further demonstrates that color congruence and contrast significantly affect conversions, trust, and engagement in nonlinear ways, highlighting the need for advanced predictive models and reinforcing the theoretical and empirical relevance of this study.

Figure 2 illustrates a comparison of the UI color selection process before and after the adoption of a data-driven design approach. This visualization aims to highlight the fundamental shift in how interface design decisions are made, particularly in UI color selection. Traditionally, UI color choices are determined based on intuition, personal experience, or designers' subjective preferences. Although this approach can produce visually appealing interfaces, the effectiveness of colors on user behavior often cannot be measured objectively.

The lack of a direct linkage between color choices and user engagement metrics, such as clicks or interactions, makes the design evaluation process limited and difficult to replicate.

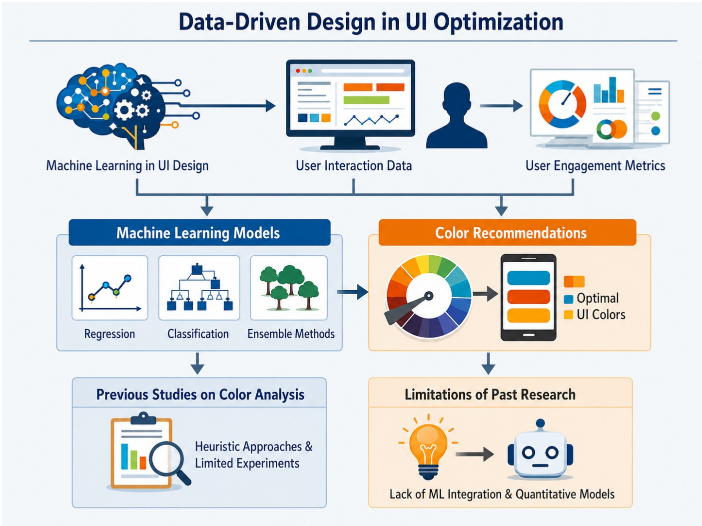

Figure 2. Data-Driven Design in UI Optimization

In addition to illustrating the shift in approach, Figure 2 Data Driven Design in UI Optimization depicts a systematic workflow for UI color selection, starting from the collection of user interaction data to analysis using machine learning models. The predictive model serves as a bridge between UI color characteristics and user engagement metrics, thereby enabling objective evaluation and prediction of color impacts. Furthermore, the figure emphasizes a continuous evaluation process, in which UI color recommendations can be iteratively updated based on the latest data to consistently enhance user engagement.

2.4. Research Gap

Although extensive research has been conducted on color theory in UI/UX and on the measurement of user engagement, most studies still address these two aspects separately. Previous research has generally focused on the psychological effects of color or on visual interface evaluation through qualitative approaches and limited experiments [31]. Meanwhile, studies on data-driven UI optimization have more often emphasized layout, navigation, or content, leaving UI color selection relatively underexplored in a systematic and in-depth manner.

Furthermore, the application of machine learning for the quantitative analysis of UI color remains very limited. Many studies continue to rely on heuristic rules or conventional methods such as A/B testing, without leveraging the capability of machine learning to model complex relationships between color characteristics and user engagement metrics. This situation indicates a significant research gap in integrating machine learning models with UI color selection [32]. Therefore, this study aims to address this gap by proposing a data-driven approach that objectively and measurably links UI color with user engagement.

3. RESEARCH METHOD

3.1. Data Collection

The data collection stage is a crucial step in this study because data quality directly affects the accuracy of the analysis and the developed models. The research collects two main types of data: user interface color data and user engagement metrics. UI color data are obtained from selected applications or websites by identifying key visual elements such as backgrounds, text, buttons, and other interactive components. These colors are extracted in standard formats such as RGB or HEX to allow quantitative analysis and provide an accurate representation of the interface design experienced by users [33]. In addition, engagement data are gathered from user interaction logs, including metrics such as number of clicks, duration of use, and interaction frequency, which are used to measure user involvement and analyze the relationship between UI colors and user behavior.

Although the dataset is collected from selected applications representing common digital interface structures, the model is designed to learn generalized visual–behavioral patterns rather than platform-specific characteristics [34]. The applications include various interface types, such as dashboard systems, transactional platforms, and content-based services. However, the dataset does not yet fully represent all industries or cultural contexts, so further cross-industry validation is recommended to strengthen the external validity and generalizability of the model.

3.2. Preprocessing

The preprocessing stage prepares raw data for analysis and machine learning by improving its quality and consistency. Initially, the dataset contains raw UI color values in RGB or HEX formats with inconsistent scales, along with user engagement logs that may include noise, missing values, duplicates, and outliers caused by recording errors or unusual behavior, as illustrated in Figure 3 UI Colour Data Preprocessing Pipeline. To address this, color values are normalized into HSL and CIELAB spaces to better represent perception attributes such as hue, saturation, and lightness. Data cleaning is then performed by removing invalid, duplicate, and extreme values, handling missing data using median imputation for numerical variables and mode imputation for categorical features, and detecting outliers using IQR and z-score analysis. These steps ensure a structured and reliable dataset for further feature engineering and machine learning modeling.

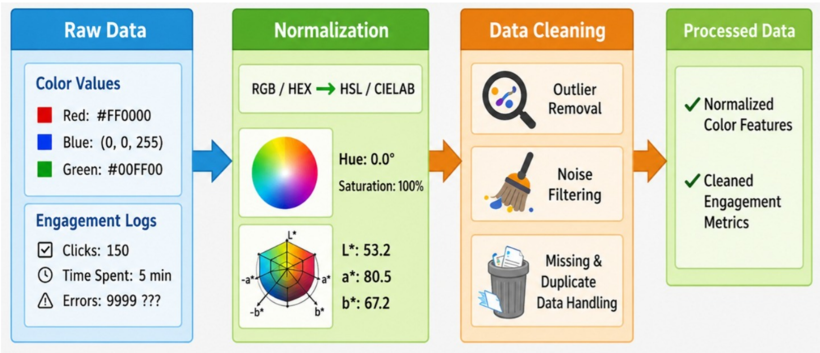

Figure 3. UI Colour Data Preprocessing Pipeline

After undergoing the preprocessing stage, as shown in Figure 3 UI Colour Data Preprocessing Pipeline, the color data are normalized by converting RGB or HEX formats into the HSL or CIELAB color spaces, making them more consistent and aligned with human visual perception. Next, data cleaning and outlier removal are performed to eliminate noise and invalid records. The result is a structured and validated dataset ready for feature engineering and machine learning modeling.

3.3. Feature Engineering

Feature engineering aims to transform the preprocessed data into meaningful features that can be effectively utilized by machine learning models. The normalized UI color values are extracted into numerical representations that capture key visual characteristics likely to influence user engagement [35]. One of the primary features is the contrast ratio, which refers to the difference in luminance between a UI element and its background and is used to assess interface readability and visibility. Good contrast is generally correlated with a more positive user experience. Another feature is the harmony score, which represents the degree of color combination harmony based on color harmony principles, such as analogous or complementary schemes, thereby reflecting the visual comfort and aesthetic quality of the UI.

Semantic color categories are used to group colors into classifications such as warm, cool, neutral, or functional meanings like alert and success to capture psychological aspects that cannot be represented by numerical color values alone [36]. By combining these semantic and perception attributes with measurable factors such as contrast and harmony, the model can better understand the relationship between UI color characteristics and user engagement, improving the accuracy of color prediction and recommendation. However, before feature engineering, the dataset only contains preprocessing results in basic color spaces such as HSL or CIELAB, which describe technical color properties but do not yet represent contrast, harmony, or psychological meaning within the interface context. Engagement metrics like click through rate are also still separated from visual attributes, making it difficult to analyze the influence of color on user behavior [37]. Therefore, feature engineering is necessary to transform these raw numerical values into structured and interpretable features that better represent visual quality and user experience for machine learning modeling.

Table 1. Contoh Hasil Feature Engineering Warna UI

UI Element	Colour (HEX)	Background (HEX)	Contrast Ratio	Harmony Score	Semantic Category	CTR
Button CTA	#1F77B4	#FFFFFF	4.8	0.82	Cool / Action	0.124
Header	#2CA02C	#F5F5F5	3.9	0.76	Cool / Success	0.098
Warning	#D62728	#FFFFFF	5.6	0.70	Warm / Alert	0.110
Link	#9467BD	#FFFFFF	4.2	0.79	Cool / Info	0.105
Card BG	#E0E0E0	#FFFFFF	1.5	0.85	Neutral	0.065

Table 1 illustrates an example of how UI color data that have undergone preprocessing are subsequently extracted into numerical and semantic features during the feature engineering stage. Each UI element is represented by its primary color and background color, from which the contrast ratio is calculated to measure readability, the harmony score is computed to assess the consistency of color combinations, and the semantic color category is assigned to represent the psychological meaning of the colors. The engagement column, such as click-through rate, is used as the target variable to be predicted by the machine learning model.

3.4. Machine Learning Model

At this stage, machine learning models are used to learn the relationships between UI color features and user engagement metrics [38]. Regression is applied to predict continuous engagement values, while classification categorizes engagement levels into predefined classes. The selected algorithms include linear and logistic regression, random forest, and XGBoost due to their complementary strengths [39]. Linear regression serves as a baseline model, whereas Random Forest and XGBoost capture nonlinear relationships and complex feature interactions, enabling a more reliable predictive framework.

3.4.1. Machine Learning Model Training and Testing Workflow

- Step 1: Dataset Preparation In this step, all data that have undergone preprocessing and feature engineering are combined into a single dataset. Features such as contrast ratio, harmony score, and semantic color categories serve as input variables, while user engagement, such as click-through rate or high low categories, is used as the target variable [40]. The purpose of this stage is to organize the data into a clean and structured format so that it can be directly utilized by machine learning algorithms.

- Step 2: Data Splitting The dataset is then divided into two subsets, namely a training set and a testing set, for example using an 80:20 ratio. The training set is used to train the model, while the testing set is used to evaluate the model's performance on previously unseen data. This split is important to ensure that the model does not merely memorize the training data, but is also capable of making accurate predictions on new data.

- Step 3: Model Training At this stage, regression or classification models are trained using the training set. The models learn the relationships between UI color features and the values or classes of user engagement through the optimization of their internal parameters. The better the quality of the data and features, the more effectively the models can capture relevant patterns [41].

- Step 4: Model Testing & Prediction After the model has been trained, the data in the testing set are used as input to generate engagement predictions. These predicted results are then compared with the actual values in the test data. This stage aims to assess how well the model can generalize to data that were not used during training.

- Step 5: Model Evaluation Tuning In the final step, model performance is evaluated using RMSE for regression and accuracy and F1-score for classification. To improve generalizability, 5-fold cross-validation is applied and hyperparameters are optimized using grid search, especially for Random Forest and XGBoost [42]. Overfitting is monitored by comparing training and validation errors. If performance is not satisfactory, tuning and retraining are conducted until the best model is achieved for reliable UI color recommendations.

After all stages of the training testing process are completed, a trained machine learning model is obtained that is capable of predicting user engagement based on UI color features. The model has been evaluated using RMSE for regression or accuracy and F1-score for classification, allowing its performance to be measured objectively and optimized through tuning. At this stage, the model is ready to be applied to predict engagement for new UI designs and to provide data-driven color recommendations. This after condition reflects a shift from a subjective approach to a more objective and measurable approach in UI color selection.

3.5. Experiment Setup

The experiment setup stage aims to validate the effectiveness of the UI color recommendations generated by the machine learning model on user engagement [43, 44]. The method employed is A/B testing, comparing two interface versions: version A uses the original colors, while version B uses the colors recommended by the model. Users are randomly assigned to the two groups, and engagement metrics such as click-through rate or interaction duration are measured to determine whether the color differences result in a significant improvement [45]. The experiment is supported by various tools and software, including Python for data processing, model training, and result analysis, as well as Figma plugins to apply color variations to UI prototypes. Additional analytics tools can be used to record user interactions during testing. With this setup, the model's predictions can be validated directly in the context of real-world usage.

To assess generalizability, the experimental design allows replication across different interface types by maintaining consistent feature extraction and evaluation procedures. This approach ensures that the model can be applied beyond a single platform and supports broader validation of the findings. However, variations in user demographics, device types, and domain-specific interaction patterns may influence engagement outcomes [46]. Consequently, future implementations should consider multi-industry datasets and cross-platform evaluations to confirm the stability of color engagement relationships across diverse digital environments.

4. RESULTS AND DISCUSSION

4.1. Model Performance

This section explains the performance of machine learning models in predicting user engagement based on UI color features using training and testing data [47]. Evaluation is conducted using RMSE for regression as well as accuracy and F1-score for classification. Several models, such as Linear Regression, Random Forest, and XGBoost, are compared to determine the best-performing algorithm. Linear Regression is used as a baseline model, while Random Forest and XGBoost are applied to capture more complex nonlinear relationships between UI color features and engagement metrics. The model with the lowest error and the highest classification scores is selected as the basis for subsequent analysis and UI color recommendation [48].

To evaluate model performance, multiple machine learning algorithms are compared using the testing data. The evaluation results are presented in Table 2, which reports RMSE values for regression tasks as well as accuracy and F1-scores for classification tasks. Linear Regression, Random Forest, and XGBoost are used to compare prediction performance and identify the most suitable model for data-driven UI color recommendations. The model with the lowest RMSE and the highest accuracy and F1-score is selected for further analysis.

Table 2. Comparison of Machine Learning Model Performance in Predicting User Engagement

Model	RMSE (Regression)	Accuracy (%)	F1-score
Linear Reg	0.145	78.2	0.77
Random Forest	0.112	84.5	0.83
XGBoost	0.098	87.3	0.86

Based on Table 2, it can be observed that the XGBoost model achieved the best performance, with the lowest RMSE and the highest accuracy and F1-score compared to the other models. This indicates that XGBoost is better able to capture the nonlinear relationships between UI color features and user engagement metrics. Meanwhile, Random Forest also demonstrated good and stable performance, but it still fell short of XGBoost. The linear model showed the lowest performance, suggesting that the relationship between UI colors and engagement is complex and cannot be fully modeled linearly [49]. Therefore, XGBoost was selected as the primary model for further analysis and as the basis for data-driven UI color recommendations.

4.2. Significant Colour Features

This section analyzes the UI color features that most strongly influence user engagement based on machine learning results and feature importance evaluation. The findings show that color combinations with high contrast between key elements such as buttons or text and the background tend to produce higher engagement, including improved CTR, longer interaction duration, and more frequent user interaction [50]. High contrast improves readability and helps users quickly recognize interactive components, while low-contrast combinations often reduce usability and engagement. In terms of color temperature, warm colors such as red, orange, and yellow effectively attract attention and are suitable for call-to-action elements, whereas cool colors like blue and green create a sense of calmness and trust, making them appropriate for backgrounds or areas requiring visual comfort [51, 52]. The model further indicates that a balanced combination of warm accent colors and cool base colors leads to more stable engagement [53]. In addition, semantic alignment between color and function, such as green for success and red for alerts, helps users interpret information more quickly. Overall, the results suggest that engagement is influenced not by a single color but by a combination of factors including contrast, color temperature balance, and functional meaning, highlighting the importance of integrating readability, psychological impact, and visual function in UI color design [54].

4.3. Visualization

This section presents the results of the analysis on the relationship between UI colors and user engagement through visualizations that help translate machine learning outputs into interpretable insights for researchers and UI design practitioners. A color engagement mapping graph illustrates the relationship between color attributes such as hue, saturation, brightness, or contrast ratio and engagement metrics like CTR and time on task, allowing identification of color ranges associated with higher engagement levels. In addition, a color correlation heatmap displays the strength of relationships between various color features, including HSB values, contrast ratio, harmony score, and semantic categories, and engagement metrics, where stronger color intensity indicates higher correlation. These visualizations help reveal key patterns and influential features that may not be evident from numerical data alone. To further validate the model, A/B testing was conducted by comparing the original color scheme (Version A) with the model-recommended configuration (Version B), where users were randomly assigned and engagement metrics such as CTR, interaction duration, and task completion were measured. The improved performance of Version B confirms the model's predictive validity and demonstrates a practical workflow for testing and refining UI color decisions based on measurable engagement outcomes.

4.4. Discussion

The findings indicate that UI colors significantly influence user engagement by improving readability, attention, comfort, and usability. High-contrast color schemes help users identify key interface elements quickly, while balanced warm–cool color combinations enhance visual comfort and trust. Warm colors attract attention and encourage action, whereas cool colors promote calmness and stability. The study also confirms color theory principles through machine learning analysis, providing objective recommendations for UI design. Additionally, semantic consistency between color and function, such as green for success and red for warnings, improves user understanding and interaction efficiency.

Unlike prior research focusing on layout or security, this study models color as a structured predictor of behavioral engagement and provides a granular computational analysis of its impact on measurable user actions across emerging digital ecosystems [55]. The findings show that effective UI color design is influenced not by a single color choice, but by the combination of contrast, harmony, semantic meaning, and psychological perception. By integrating machine learning with UI design principles, this research moves beyond subjective designer intuition and offers a predictive framework for consistent and scalable design decisions. Practically, designers can apply high-contrast warm colors for primary actions and cool tones for secondary elements, as well as use semantic color mapping (e.g., green for confirmed, red for failed, yellow for pending transactions) to enhance clarity and usability. This approach supports better user retention, stronger engagement, and improved overall digital product performance.

5. MANAGERIAL IMPLICATIONS

This section provides practical guidance for UI designers and developers to select colors based on data-driven findings rather than subjective intuition. Key principles include maintaining high contrast, balancing warm and cool colors, and applying semantic color categories such as green for success and red for alerts. By using machine learning predictions and iterative evaluation, designers can improve user engagement more efficiently and consistently across digital products.

The managerial implications are particularly significant for industries where clarity and trust are critical, such as blockchain platforms, fintech, healthcare, and other transactional systems. In decentralized applications (dApps), crypto wallets, and smart contract interfaces, optimized color selection enhances the visibility of transaction states (e.g., pending, verified, failed), strengthens user trust, and reduces cognitive load. From a business perspective, improved engagement contributes to higher retention, increased interaction time, and stronger conversion performance. Beyond individual projects, organizations can institutionalize data-driven color validation within UI governance policies, establishing standardized contrast thresholds, semantic consistency, and measurable engagement benchmarks to align visual strategy with quantifiable user behavior outcomes.

6. CONCLUSION

This study shows that data-driven UI color selection can improve user engagement by using a machine learning model to analyze relationships between color features such as contrast ratio, harmony score, hue, and semantic categories and engagement metrics like click-through rate and interaction duration. Visualization results, including color engagement mapping and correlation heatmaps, reveal clear patterns, particularly the effectiveness of high contrast and balanced warm–cool color combinations in increasing engagement. These findings provide practical guidance for designers through measurable criteria such as contrast levels, semantic alignment, and color balance that can be integrated into UI design systems and digital product workflows.

The research questions regarding which colors most effectively increase engagement and how data can guide UI color decisions were addressed through quantitative analysis. The results show that high-contrast colors, proper semantic color use, and balanced warm–cool tones produce the highest engagement. However, the study has limitations, including a dataset drawn from limited applications and a focus only on color features without considering other design factors such as layout or typography. Despite this, the proposed framework offers a transferable foundation for implementation across industries such as e-commerce, blockchain platforms, and mobile applications.

Future research is recommended to expand the dataset across more platforms and user groups and to incorporate additional UI elements such as typography, iconography, and animation. Developing more advanced or adaptive machine learning models could also enable real-time color recommendations based on dynamic user behavior. From a practical perspective, organizations can adopt a structured workflow involving engagement data collection, color feature normalization (e.g., HSL or CIELAB), model training, integration into design tools, and validation through A/B testing. This approach transforms UI color selection from a subjective choice into a measurable and evidence-based design strategy that can enhance digital product performance.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: SS, TN, and HZ; Methodology: FP; Software: TN; Validation: FP and HZ; Formal Analysis: SS and TN; Investigation: FP; Resources: HZ; Data Curation: TN; Writing Original Draft Preparation: SS and HZ; FP Writing Review and Editing: HZ; Visualization: TN; All authors, SS, TN, FP, and HZ have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] T. Williams, E. Kallas, E. Garcia, A. Fitzroy, and P. Sithole, "International business expansion strategies: A data-driven approach with ibm spss," *APTISI Transactions on Management*, vol. 8, no. 2, pp. 131–138, 2024.

[2] Q. Sun, Y. Xue, and Z. Song, "Adaptive user interface generation through reinforcement learning: A data-driven approach to personalization and optimization," in *2024 6th International Conference on Frontier Technologies of Information and Computer (ICFTIC)*. IEEE, 2024, pp. 1386–1391.

[3] A. Mogra, P. K. Pandey, and R. S. Panwar, "Artificial intelligence enabled sleep health dashboards: Power bi integration for data-driven lifestyle modifications," in *2024 Eighth International Conference on Parallel, Distributed and Grid Computing (PDGC)*. IEEE, 2024, pp. 535–539.

[4] T. Myllynen and E. Kamau, "The evolution of dashboard design: Best practices for data visualization in decision support systems," 2025.

[5] X. Bao, "Deep learning-driven personalized recommendations and layout optimization for ui interaction design: X. bao," *Progress in Artificial Intelligence*, pp. 1–19, 2025.

[6] D. Kundana *et al.*, "Data driven analysis of borobudur ticket sentiment using naïve bayes." *Aptisi Transactions on Technopreneurship (ATT)*, vol. 5, no. 2sp, pp. 221–233, 2023.

[7] R. Grande, J. Albusac, S. S. Sobrino, D. Vallejo, and J. J. Castro-Schez, "Gamifying virtual reality shopping experiences: a case study on a real-world scenario," *Virtual Reality*, 2026.

[8] R. A. Ruddro, "Energy efficiency monitoring in institutional facilities: A review of ui/ux solutions for iot dashboards," *International Journal of Scientific Interdisciplinary Research*, vol. 6, no. 1, pp. 137–162, 2025.

[9] A. Rahim, S. H. Suryawan *et al.*, "Optimizing ui/ux of aimscore application with design thinking to enhance user interaction and engagement," *Teknika*, vol. 14, no. 2, pp. 205–212, 2025.

[10] U. Rahardja, S.-C. Chen, Y.-C. Lin, T.-C. Tsai, Q. Aini, A. Khan, F. P. Oganda, E. R. Dewi, Y.-C. Cho, and C.-H. Hsu, "Evaluating the mediating mechanism of perceived trust and risk toward cryptocurrency: An empirical research," *SAGE Open*, vol. 13, no. 4, p. 21582440231217854, 2023.

[11] C. J. Weber, J. Huang, and S. Rothe, "Drawing-in-steps: Supporting creative goals through user engagement via hierarchical image generation," in *Proceedings of the 2025 ACM International Conference on Interactive Media Experiences*, 2025, pp. 108–125.

[12] C. Whyte, M. D. O'Toole, A. J. Casson, and E. Gowen, "A feasibility study of data driven ecological momentary assessment surveys using smart wearables to capture emotions," in *2024 IEEE Sensors Applications Symposium (SAS)*. IEEE, 2024, pp. 1–6.

[13] T. Marbun, S. Baltasar, and E. Ahman, "Technology implementation on objectives and key results in pt. pos indonesia 2020-2024 period," *International Journal of Cyber and IT Service Management*, vol. 5, no. 1, pp. 45–57, 2025.

[14] T. Dessie, "Designing personalized coffee experiences in modern e-commerce for enhanced user engagement and sales," 2025.

[15] L. Meria, S. Hidayat, N. D. Santiago, S. Saukani, and S. H. Khotimah, "Blending work values, engagement, and satisfaction to drive ocb in technopreneurial startups," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 6, no. 3, pp. 324–338, 2024.

[16] Y. Liu, H. Tan, G. Cao, and Y. Xu, "Enhancing user engagement through adaptive ui/ux design: A study on personalized mobile app interfaces," *Computer Science & IT Research Journal*, vol. 5, no. 8, pp. 1942–1962, 2024.

[17] E. E. Djajasasana and J. R. K. Bokau, "Utilization of micro influencers and engagement in social media to gain cadet candidates," *ADI Journal on Recent Innovation*, vol. 6, no. 1, pp. 1–7, 2024.
[18] K. ZIOBRO, "User-centered dashboard design-leveraging design thinking and game design principles for improving user engagement," 2024.
[19] J. Dai, X. Mao, P. Wu, H. Zhou, and L. Cao, "Revolutionizing cross-border e-commerce: A deep dive into ai and big data-driven innovations for the straw hat industry," *Plos one*, vol. 19, no. 12, p. e0305639, 2024.
[20] A. Upadhyay, M. Shekhawat, and R. Manhas, "Data driven ux/ui design for reproductive health tracker," in *2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*. IEEE, 2023, pp. 1–5.
[21] E. Höglin Forsberg and A. Tarafar, "Investigating the influence of visual consistency between sns content and ui design on user experience: A data-driven approach to the integration of ui and sns visual content," 2025.
[22] F. Rahardja, L. K. Choi, R. C. Wijaya, and R. A. Sunarjo, "Gamification in digital startups: Enhancing user engagement and business growth," *Startupreneur Business Digital (SABDA Journal)*, vol. 4, no. 1, pp. 1–11, 2025.
[23] S. Feng, S. Ma, H. Wang, D. Kong, and C. Chen, "Mud: Towards a large-scale and noise-filtered ui dataset for modern style ui modeling," in *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, 2024, pp. 1–14.
[24] Y. Yu, L. Ma, X. Chen, and Y. Zhong, "Ui design optimization method based on user behavior analysis-based on heat map analysis, k-means clustering, and random forest regression analysis algorithms," *J. COMBIN. MATH. COMBIN. COMPUT*, vol. 127, pp. 6309–6324, 2025.
[25] M. Gusia, "The application of color theory in ui/ux design," 2024.
[26] J. W. Nybom *et al.*, "Data-driven approaches to narrative personalisation through psychologically motivated models," Ph.D. dissertation, University of the Arts London, 2024.
[27] S. Watini and W. Setyowati, "Using gamification to increase e-learning engagement," *International Transactions on Education Technology (ITEE)*, vol. 1, no. 2, pp. 84–94, 2023.
[28] K. Alfatmi, S. Chaitanya, A. Ashiya, S. Sakshi, and V. Sarvagya, "Data-driven decisions: How integrated machine learning and visual dashboards are transforming business," in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*. IEEE, 2024, pp. 1–7.
[29] N. Gupta, "Data-driven storytelling: How to use data to tell compelling stories and drive business outcomes," *World Journal of Advanced Engineering Technology and Sciences*, vol. 8, no. 1, pp. 497–509, 2023.
[30] J. Qu, Y. Zhang, W. Tang, W. Cheng, Y. Zhang, and L. Bu, "Developing a virtual reality healthcare product based on data-driven concepts: A case study," *Advanced Engineering Informatics*, vol. 57, p. 102118, 2023.
[31] A. Shankar and A. Behl, "How to enhance consumer experience over mobile wallet: a data-driven approach," *Journal of Strategic Marketing*, vol. 31, no. 4, pp. 838–855, 2023.
[32] D. Indriyani and L. Meria, "Influence of work environment and work characteristics on turnover intention system with mediation role of work engagement," *International Journal of Cyber and IT Service Management (IJCITSM)*, vol. 2, no. 2, pp. 127–138, 2022.
[33] L. Bunnik, "Data-driven decision-making: A graphical user interface for real-time market analysis & quotation evaluation visualising and comparing internal & external data using r shiny," Master's thesis, 2023.
[34] O. Kharakhash, "Data visualization: transforming complex data into actionable insights." *Automation of Technological & Business Processes/Avtomatizaciâ Tehnologiceskih i Biznes-Processov*, vol. 15, no. 2, 2023.
[35] M. Burgermaster, P. M. Desai, E. M. Heitkemper, F. Juul, E. G. Mitchell, M. Turchioe, D. J. Albers, M. E. Levine, D. Larson, and L. Mamykina, "Who needs what (features) when? personalizing engagement with data-driven self-management to improve health equity," *Journal of biomedical informatics*, vol. 144, p. 104419, 2023.
[36] M. Koenraad, "Data-driven decision-making: real-time construction market monitoring to enhance operational efficiency," Master's thesis, 2023.
[37] K. Mirdad, O. Daeli, N. Septiani, A. Ekawati, and U. Rusilowati, "Optimizing student engagement and

performance usingai-enabled educational tools," *Journal of Computer Science and Technology Application*, vol. 1, no. 1, pp. 53–60, 2024.

[38] U.S. Department of Justice, "Guidance on web accessibility and the ada," https://www.ada.gov/resources/web-guidance/, 2022.

[39] Y. He, A. Pereira, and T. Kucherenko, "Evaluating data-driven co-speech gestures of embodied conversational agents through real-time interaction," in *Proceedings of the 22nd ACM International Conference on Intelligent Virtual Agents*, 2022, pp. 1–8.

[40] M. Talluri, N. R. Rachamala, R. Malaiyalan, N. Memon, and S. S. Palli, "Cross-platform data visualization strategies for business stakeholders," *Lex Localis*, vol. 23, no. S3, pp. 1–12, 2025.

[41] J. Chang, X. Lei, Z. Wan, and L. Huang, "Dynamic optimization for in-app advertising games: A data-driven methodology validated with field experiments," *Available at SSRN*, 2026.

[42] O. Joseph, A. Akintola, E. Offiong, O. Olajuwon, U. Offia, and A. Faniyan, "Ai-enhanced consumer insights: Leveraging behavioural analytics for hyper-personalised marketing strategies," *J Artif Intell Mach Learn & Data Sci 2025*, vol. 3, no. 1, pp. 2361–2368, 2025.

[43] B. Murugesan, K. Jayanthi, and G. Karthikeyan, "Integrating digital twins and 3d technologies in fashion: advancing sustainability and consumer engagement," in *Illustrating digital innovations towards intelligent fashion: Leveraging information system engineering and digital twins for efficient design of next-generation fashion*. Springer, 2024, pp. 1–88.

[44] R. Royani, S. D. Maulina, S. Sugiyono, R. W. Anugrah, and B. Callula, "Recent developments in healthcare through machine learning and artificial intelligence," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 1, pp. 86–94, 2024.

[45] S. Atef, I. Ali, A. Romouzy-Ali, M. Kato, and A. B. Eltawil, "A proposed human-ai collaborative kansei engineering methodology for heritage-inspired designs: a study using surveying and eye-tracking with africans and asians," *Journal of Engineering Design*, pp. 1–40, 2026.

[46] X. Wang, L. Xu, J. Li, C. Cheng, and L. Yu, "How background colour shapes digital text-information processing: A fnirs-eye tracking study," *International Journal of Human–Computer Interaction*, vol. 42, no. 3, pp. 1427–1441, 2026.

[47] A. Abudaqa, R. A. Alzahmi, M. F. Hilmi, and H. AlMujaini, "Impact of job security, career advancement and employee participation on employee engagement in oil and gas industry, uae," *Universidad y Sociedad*, vol. 15, no. 3, pp. 26–36, 2023.

[48] A. Gamlen, S. Goodwin, and X. Ho, "Variable mapper: Developing, implementing, and evaluating an online tool for multidimensional spatial data visualization," *Journal of Geovisualization and Spatial Analysis*, vol. 9, no. 1, p. 18, 2025.

[49] A. O. Ibitoye, O. Kolade, and O. F. Onifade, "Customer retention model using machine learning for improved user-centric quality of experience through personalised quality of service," *Journal of Business Analytics*, pp. 1–19, 2025.

[50] S. Kandel, A. C. Stumpf, A. Joshi, S. Sharma, L. E. Taylor, A. J. Jefferson, and M. A. Kenney, "Comparing flood inundation map features and diagnosing decision support design challenges," *Hydrological Processes*, vol. 40, no. 1, p. e70362, 2026.

[51] A. Basu, S. Paul, S. Ghosh, S. Das, B. Chanda, C. Bhagvati, and V. Snasel, "Digital restoration of cultural heritage with data-driven computing: A survey," *IEEE access*, vol. 11, pp. 53 939–53 977, 2023.

[52] U. Rahardja, M. Budiarto, K. Lutfiyah, O. F. P. Wahyudi, I. K. H. Azz, N. Azizah, and D. Julianingsih, "Analysis of the effectiveness of visual language and narrative in conveying value propositions in pitching decks," *International Transactions on Artificial Intelligence*, vol. 3, no. 2, pp. 161–170, 2025.

[53] Z. I. Khan, "Exploring the influence of aesthetic design on user engagement in libraries: A quantitative analysis of uae librarians' perspectives," *Journal of Librarianship and Information Science*, p. 09610006251335312, 2025.

[54] S. Strukova and J. A. Ruipérez-Valiente, "A framework for data-driven computer-based diagnostics of competencies and capabilities across contexts," in *Computer-Based Diagnostics and Systematic Analysis of Knowledge: Critical Reflections and Advancements*. Springer, 2025, pp. 57–81.

[55] X. Liang, "Ai-driven culturally aware interactive visualization: A design methodology for cross-cultural user experience," *Annals of the New York Academy of Sciences*, vol. 1556, no. 1, p. e70198, 2026.