

Small Physical Storefront Attention & Aesthetics Analysis with Neuromarketing Techniques, with AI Latent Display Attributes Tagging for Improvements

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Abstract—This research explores the role of storefront design in small business marketing, focusing on the challenges and opportunities that small businesses face in optimizing their storefronts. Storefronts are critical, as they represent the first point of contact between a business and potential customers, significantly influencing visibility, foot traffic, brand recognition, and customer acquisition. Despite their importance, many small business owners struggle to create effective storefronts due to limited resources, expertise, and access to advanced marketing tools. As a result, their storefront designs often fail to capture the attention of passersby, particularly in highly competitive retail environments. In recent years, neuromarketing techniques, particularly attention heatmaps derived from eye-tracking studies, have gained prominence for evaluating consumer visual attention and behavior. These techniques, grounded in neuroscientific principles, identify the visual elements that capture the most attention, enabling businesses to improve their storefronts for greater impact. This research applies neuromarketing tools to analyze the visual attention patterns associated with small business storefronts. The study first evaluates the aesthetic and visual quality of these storefronts before applying neuromarketing analysis to assess the attention they attract. Traditional AI models, such as PaQ-2-PiQ and NIMA, are effective at evaluating the overall aesthetic and perceptual quality of images but do not explicitly map attention distribution across storefronts. Neuromarketing outputs, such as heatmaps, provide specific insights into the areas that captivate the viewer's gaze, allowing for more targeted design improvements. For example, heatmaps can reveal the most visually prominent areas of a storefront, suggesting modifications such as repositioning signage or adjusting color contrasts to increase visibility. One of the significant advantages of this research is its focus on the accessibility of neuromarketing tools for small businesses. Traditional neuromarketing technologies are often costly, but platforms such as Neurons AI offer affordable solutions that provide similar attention insights, making these advanced tools more accessible to smaller enterprises. By integrating image-quality metrics with attention data, small business owners can make data-driven decisions to optimize their storefront designs. The study identifies several key factors that influence attention, such as clear signage, strong branding, and welcoming entrance designs, which correlate with higher attention scores. In contrast, cluttered visuals, poor lighting, and inconsistent branding are identified as common shortcomings that detract from a storefront's effectiveness. The findings suggest that combining AI-driven quality evaluation with neuromarketing heatmap data provides a comprehensive approach to storefront optimization. In conclusion, the research demonstrates that

small businesses can significantly improve the effectiveness of their storefront designs by utilizing neuromarketing insights. When small business owners prioritize attention patterns and aesthetic quality, they can improve the appeal of their storefronts and increase customer engagement, leading to more effective marketing outcomes. This approach empowers small businesses to make informed, actionable design decisions, even with limited resources, resulting in more engaging and effective storefronts.

Keywords—Neuromarketing, AI, ML, SMB

I. INTRODUCTION

Storefronts serve as critical marketing instruments for small businesses, functioning as the primary point of engagement between a small enterprise and its prospective customers. An effective storefront design can substantially improve visibility, increase foot traffic, and contribute to brand recognition and customer acquisition. Despite this importance, many small business owners struggle to optimize their storefronts, often due to limited resources, insufficient expertise, or a lack of access to advanced marketing tools. These constraints frequently result in storefront designs that fail to attract the attention of passersby, especially in highly competitive retail environments.

Neuromarketing techniques (Gill & Singh, 2020; Dimpfel, 2015; Rawnaque *et al.*, 2020), most notably attention heatmaps (Ungureanu, 2017; Pfeiffer & Memili, 2016) derived from eye-tracking studies, have gained recognition as effective methods for examining consumer visual attention and behavior. Leveraging neuroscientific principles, these techniques identify the visual elements that draw the most attention, enabling businesses to enhance their designs for maximum impact. However, practical implementation is often hindered by high costs, specialized equipment, and technical complexity, making such methods less accessible for small businesses.

Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) offer promising alternatives to conventional neuromarketing practices. Specifically, models such as the Neural Image Assessment (NIMA) (Talebi & Milanfar, 2018) and PaQ-2-PiQ (Ying, 2020) have proven capable of evaluating image quality and predicting

perceptual attributes that influence human attention. Moreover, platforms like Neurons AI (Alvino, 2020) can simulate human eye focus, generating insights into the likely areas of attention without requiring a physical eye-tracking apparatus.

This research seeks to bridge the gap between the need for effective storefront optimization and the challenges small businesses face in accessing advanced marketing analytics. The objectives are threefold:

- (1) To analyze the key shortcomings and insights of existing storefront designs, using a dataset of 144 images collected from small businesses in the California Bay Area.
- (2) To explore the potential of AI models, including NIMA and PaQ-2-PiQ in assessing storefront image quality and predicting areas of visual attention.
- (3) To develop and evaluate an AI-based model as a cost-effective alternative to neuromarketing tools, achieving a higher accuracy rate in predicting visual attention insights and providing actionable recommendations for improvement.

This study shows the ability of AI models to predict visual attention and deliver design recommendations, which supports the democratization of advanced marketing analytics. The proposed AI-based strategy offers small business owners a practical, accessible mechanism for optimizing their storefronts, thus bolstering their competitive position in the marketplace.

The dataset encompasses diverse storefronts from various sectors, including restaurants, cafes, and retail outlets. Each image was analyzed using NIMA for image quality scores and PaQ-2-PiQ for local and global perceptual assessments. In addition, the Neurons tool was employed to simulate human eye focus, generating attention heatmaps that revealed critical visual components of each storefront.

Preliminary findings indicate that AI models effectively replicate insights typically derived from neuromarketing. Elements such as clear signage, strong branding, and welcoming entrance designs correlate with higher attention scores. Conversely, cluttered visuals, inadequate lighting, and inconsistencies in branding were identified as prevalent shortcomings.

II. PRIOR RESEARCH

The appearance and configuration of a storefront significantly influence consumer perceptions and decisions regarding whether to enter a retail establishment (Bitner, 1992). Acting as a non-verbal medium, a storefront conveys a brand's identity, values, and offerings. Previous studies have explored storefront design, consumer visual attention, and AI applications in image analysis. This section provides an overview of the literature that informs the present research.

A. Importance of Storefront Design in Consumer Behavior

Storefront aesthetics have a substantial impact on consumer attraction and behavior. Elements such as signage clarity, architectural style, color schemes, and façade design collectively shape the store's visual impression (Kerfoot, 2003). Clear, prominent signage aids in rapid information processing, enabling potential customers to efficiently

identify a store's offerings (Chebat, 2005). Research by underscores that distinctive, well-designed storefronts enhance brand recognition and improve customer recall (Das & Varshneya, 2017).

Additional findings indicate that consumers are particularly drawn to storefronts perceived as visually appealing and conveying a sense of quality (Levy *et al.*, 2019). A study revealed how façade design can influence emotional responses, ultimately affecting shopping intentions (Quartier *et al.*, 2014). With their limited marketing budgets, small businesses rely heavily on a strong storefront presence to attract walk-in customers (Parsa *et al.*, 2015).

B. Visual Attention and Neuromarketing Techniques

Insights into how consumers allocate their visual attention on a storefront can drive design optimization. Neuromarketing strategies, particularly eye-tracking and attention heatmaps, are employed to capture consumer gaze patterns (Wedel & Pieters, 2008). Eye-tracking research finds that individuals tend to fixate on high-information areas, including logos, promotional signage, and entrance points (Clement *et al.*, 2013).

Nevertheless, small businesses face challenges in adopting neuromarketing methods due to the prohibitive cost of equipment and specialized expertise (Plassmann *et al.*, 2012). Consequently, there is a need for more accessible approaches that can produce comparable insights without significant financial or technical burdens.

C. Artificial Intelligence in Image Quality and Attention Prediction

Advances in AI and ML have opened new avenues for analyzing visual content and forecasting human attention patterns. AI models can assess image quality and aesthetic appeal by leveraging large, labeled datasets (Talebi & Milanfar, 2018). For instance, NIMA evaluates images based on predicted aesthetic and technical qualities, aligning closely with human perception (Talebi & Milanfar, 2018). Similarly, PaQ-2-PiQ estimates perceptual image quality using both local and global features (Ying *et al.*, 2020). While these models have been applied in fields such as photography and image enhancement, their role in optimizing retail storefronts remains under-examined.

AI-based saliency models offer an additional method for estimating where a viewer's gaze is likely to dwell in an image (Kümmerer *et al.*, 2016). These models, such as DeepGaze II, employ deep neural networks to produce predictive heatmaps of attention. This approach provides a cost-effective alternative to conventional neuromarketing tools, making advanced visual analysis accessible to smaller enterprises.

D. Application of AI in Retail Contexts

While AI research in retail has largely focused on customer experience, personalized recommendations, and inventory management (Grewal *et al.*, 2017), there are fewer investigations into the application of AI models for storefront design. Huang and Benyoucef (2013) demonstrated a positive correlation between AI-based visual merchandising predictions and consumer preferences. For small businesses, AI-based approaches can supply cost-effective, actionable

insights into how design elements influence consumer attention (Daugherty *et al.*, 2018).

E. Gaps in Existing Research

Existing neuromarketing case studies have provided valuable insights into how consumer attention is influenced by storefront elements. For instance, one study found that visual saliency plays a significant role in shaping consumer decision-making in retail environments, with high-contrast signage and strategic product placement increasing consumer engagement (Milosavljevic *et al.*, 2011). Similarly, a study on *The Buffer Effect* demonstrated how eye-tracking technology has been leveraged by major retail brands to optimize shelf layouts and in-store displays (Wedel & Pieters, 2015).

Despite acknowledgment of the importance of storefront design and recent strides in AI technology, there is a noticeable gap in studies that integrate these domains for small businesses. Specifically, limited empirical research has examined the capability of AI models (e.g., NIMA and PaQ-2-PiQ) to predict consumer attention specifically for physical storefronts. Moreover, there has been little exploration into how AI-driven findings can be practically applied to enhance storefront presentations. Historically, research has centered on large retail chains or theoretical modeling, with minimal real-world application (Huang & Rust, 2021). Consequently, an opportunity exists to validate these methods in practical, small-business scenarios.

III. DATA COLLECTION AND METHODOLOGY

A. Data Collection

A total of 144 storefront images were gathered from small businesses across the California Bay Area, San Francisco (Metropolitan Transportation Commission). Figure 1a depicts store densities by city, with San Jose representing the highest density (75 stores), followed by Santa Clara (22) and Sunnyvale (14). The selection prioritized diversity in size, type, and branding, encompassing restaurants, cafes, and retail establishments. Figure 1b illustrates the distribution of store types: 49.3% restaurants, 27.1% salons, and 23.6% retail.

To maintain consistency, all images were captured from a frontal angle, ensuring unobstructed views of each storefront’s entrance, signage, and façade. Blurred or obstructed images were excluded to maintain a uniformly high standard of quality.

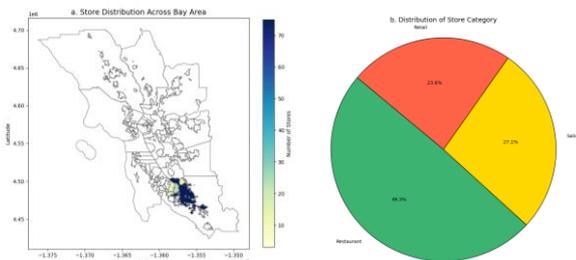


Fig. 1. The distribution of sample stores and image quality categories

B. Data Compilation Steps

1) Image acquisition

Storefront photographs were taken in the field, ensuring sufficient resolution to evaluate factors like signage clarity,

color contrast, and window displays.

2) Metadata annotation

Each image was assigned a unique identifier. Key attributes recorded included URL, Image_Name, Folder_Name, Store_Name, Store_Category, and Store_Location.

This comprehensive labeling facilitated cross-referencing during subsequent analyses.

3) Quality checks

Images were reviewed for clarity, correct orientation, and freedom from significant distortions. Those failing to meet the criteria were removed from the dataset.

C. Methodology

The primary goal of this research was to evaluate storefront designs through AI-based models and human-in-the-loop assessments, identifying strengths, attention hotspots, and potential areas for improvement.

1) Image quality assessment

Two established AI models were utilized to evaluate the aesthetic and perceptual quality of each storefront image:

a) PaQ-2-PiQ (Perceptual Image Quality) Model

This model provides both local and global quality metrics, classifying images into four categories (i.e., “Good,” “Excellent,” “Fair,” and “Poor”). Figure 2 shows the distribution of image quality classes, indicating a predominance of “Good” and “Excellent” categories (n = 50 each), compared to lower-quality ratings (“Poor” and “Fair” totaling 19 and 25, respectively).

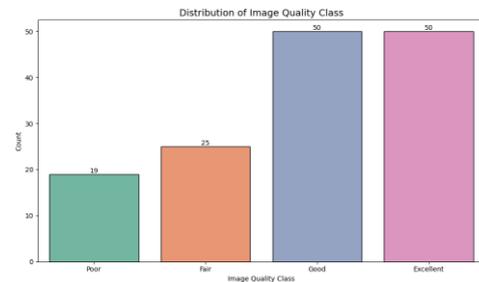


Fig. 2. The distribution of image quality class.

b) NIMA (Neural Image Assessment) Model

This model generates a continuous aesthetic score based on likely human perceptions of visual appeal. Figure 3 illustrates NIMA scores by score category: restaurants, retail, and salons, demonstrating generally consistent quality among them. Salons showed notably higher local scores and median global scores, suggesting a stronger visual impact in localized aesthetics.

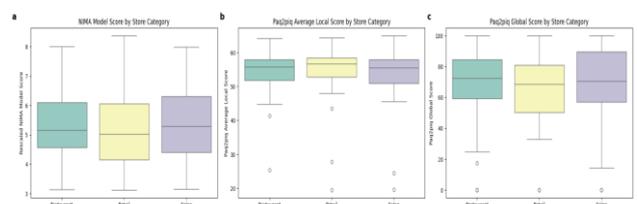


Fig. 3. Image quality score distribution by store category.

2) Neuromarketing annotation and neurons AI

a) Attention Heatmaps

To supplement the AI-based evaluations of image quality,

neuromarketing tools were used to produce heatmaps identifying the areas within each storefront image most likely to capture consumer attention.

b) *Neurons AI*

As a specialized neuromarketing software platform, Neurons AI was employed to simulate eye-tracking and generate predicted focal point predictions. This approach provided insights into consumer attention hotspots without requiring on-site experiments.



Fig. 4. Examples of storefront image prior version(left) and post neurons version(right).

IV. NEUROMARKETING TECHNIQUES AND AI MODELS

A. Overview of Neuromarketing Tools

Neuromarketing methods apply neuroscience to marketing research to reveal subconscious consumer responses. In the context of storefront optimization, attention heatmaps generated from simulated or actual eye-tracking data highlight the visual features, such as signage, entrances, or bold color contrasts, that instinctively draw consumer attention. These insights enable businesses to refine design elements to strengthen brand visibility and increase foot traffic.

In this study, neuromarketing data derived from AI-driven attention analyses were integrated with AI-based image quality scores to identify potential design flaws and propose evidence-based enhancements. By pinpointing visual focal points, small enterprises can optimize their storefront displays to more effectively capture public interest.

B. *Neurons Software Technique*

Image Collection and Processing (Specific to Neuromarketing):

1) *Image upload*

Each of the 144 images was uploaded to a neuromarketing software platform (including Neurons AI) that produces attention heatmaps.

2) *Automated processing*

The platform’s AI-driven system evaluated each image to identify high-interest areas, based on features such as signage position, color contrast, and textual clarity.

3) *Heatmap generation*

Color-coded heatmaps were generated, highlighting “hotspots” (regions of high attention) and cooler zones (areas less likely to attract the viewer’s gaze).

4) *Storing and organizing processed images*

Screenshots of all heatmaps were cataloged and aligned with the AI-based quality scores for subsequent integrated

analysis.

C. *Neurons AI: Revolutionizing Marketing with AI-Powered Insights*

Neurons AI integrates behavioral science, neuroethics, and deep learning to optimize visual materials.

1) *Core functionality*

AI-Powered Analysis: The platform processes images, videos, and textual elements to predict user attention, emotional engagement, and conversion potential.

Rapid Feedback: Near-real-time suggestions are provided based on extensive neuromarketing data.

2) *Workflow*

a) *Upload:* Storefront images or visual creatives are sent to the Neurons AI platform.

b) *Recommendations:* The tool assesses design clarity, text readability, and brand placement, then offers adjustments to enhance engagement.

c) *Implementation:* Store owners can apply these AI-driven improvements, such as rethinking color placement or resizing signage, to enhance storefront appeal.

3) *Behavioral Science foundation*

a) *Neuro-Behavioral Data:* The platform leverages over two decades of research, identifying emotional or cognitive triggers in visual stimuli.

b) *Diverse Applications:* From enterprise-level advertising to small business storefronts, Neurons AI tailors its insights to specific contexts.

V. RESULTS AND ANALYSIS

A. *Three Types of Keyword Tagging*



Fig. 5. Initial keyword analysis: Strengths, focus areas, and suggestions.



Fig. 6. Enhanced keyword analysis: Strengths, focus areas, and suggestions.



Fig. 7. Neuron keyword analysis: Strengths, observations, and suggestions.

1) *Strengths across analyses*

The consistent emphasis on “bold signage,” “clear branding,” and “service clarity” across all three analyses (Initial, HyperParameter, and Neuron) highlights the importance of visually strong and professional storefront elements. These attributes form the foundation of effective customer engagement.

Additional strengths, such as “signage inviting” and “branding appealing,” especially present in the Neuron and HyperParameter analyses, suggest the role of enhanced aesthetics in creating a welcoming environment.

2) Focus areas

Across all analyses, “signage focus” and “logo focus” dominate as primary areas of customer attention, reflecting the significance of clear and prominent visual elements.

Unique observations, such as the “entrance area” and “seating area,” identified in the Neuron and HyperParameter analyses, indicate a growing emphasis on functional and customer-centric design features.

3) Improvement opportunities

Recommendations such as “enhance lighting,” “visibility improvement,” and “window simplification” are consistently identified, underscoring the universal need for better lighting and visual clarity.

The Neuron analysis uniquely highlights “evening visibility” and “presentation enhancement,” indicating specific opportunities to optimize storefronts for varying times of day and customer needs.

4) Progressive refinement

The transition from the Initial to HyperParameter and Neuron analyses reveals progressively deeper and more targeted insights. These include enhanced focus on aesthetic elements (e.g., “neon focus”) and tailored recommendations for visibility and lighting improvement.

Collectively, these three analyses consistently underline the importance of clear, bold signage and strong branding as essential strengths, while identifying lighting, visibility, and tailored design features as key areas for improvement. The insights can guide strategic enhancements to boost customer engagement and elevate storefront appeal.



Fig. 9. Storefront perception across store categories: Strengths, focus areas, and suggestions.

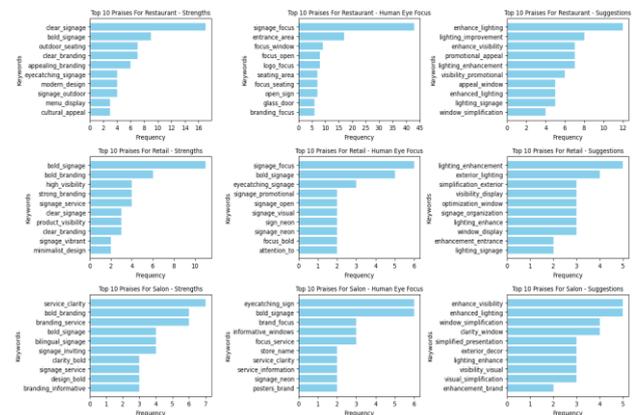


Fig. 10. Store category-based keyword frequency analysis: Strengths, focus areas, and suggestions.

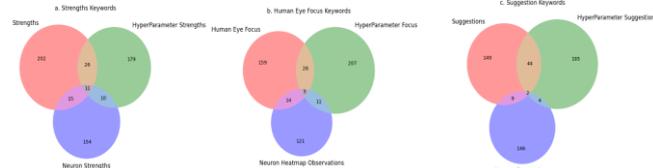


Fig. 8. Overlap and uniqueness in strengths, focus, and suggestion keywords.

Fig. 8 shows three Venn diagrams illustrating the overlap and uniqueness of keywords classified into Strengths, Focus Areas, and Suggestions, as identified by the Initial, Hyperparameter-enhanced, and Neuron models. The Neuron model consistently captures the largest number of unique keywords across all categories. The HyperParameter model also contributes significantly, particularly in the Suggestions category, with a notable overlap of 44 keywords.

A core set of common insights is evident in the small intersections across the models, including the 11 overlapping keywords for Strengths and 5 for Focus. These findings suggest that each model contributes complementary insights, and their integration offers a more comprehensive and nuanced understanding of storefront strengths, customer focus areas, and actionable improvements.

B. Keywords among Three Store Categories

Let us now examine how the three types of keyword analyses reveal distinct insights across different store categories.

1) Strengths

Common strengths across all store categories include “bold signage” and “clear branding,” highlighting their universal importance in establishing a professional and appealing storefront.

Category-specific strengths, such as “outdoor seating” for restaurants and “bilingual signage” for salons, cater to specific customer needs.

2) Human eye focus

Keywords such as “signage focus” and “branding focus” dominate attention across all categories, indicating the central role of signage and branding in capturing attention.

Additional focal points, such as “entrance area” in restaurants and “informative windows” in salons, highlight customer preferences for clarity and functionality.

3) Suggestions for improvement

“Lighting enhancement” and “visibility improvement” are consistent recommendations across categories, emphasizing the need for better illumination and visual clarity.

Category-specific suggestions include exterior lighting” for retail stores and “window simplification” for salons, pointing to the value of customizing visual strategies based on store type.

This analysis underscores the balance between maintaining universal storefront strengths (e.g., signage, branding) with targeted improvements that address the unique characteristics and customer needs of each retail category.

C. Keywords Among Four Image Quality Levels



Fig. 11. Storefront perception across image quality levels: Strengths, focus areas, and suggestions.

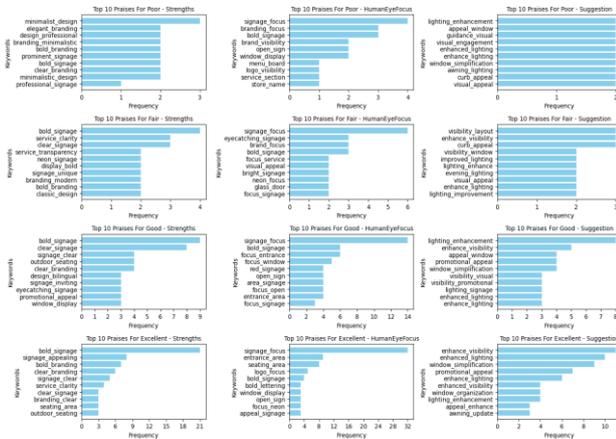


Fig. 12. Keyword frequency analysis across storefront image quality levels.

1) Strengths across levels

“Bold signage” and “clear branding” are identified as strengths across all image quality levels, emphasizing the universal importance of visually appealing and professional storefront elements.

High-performing (“Excellent”) stores also exhibit “service clarity” and “signage appealing,” showcasing their ability to provide a well-rounded and engaging customer experience. In contrast, lower-performing (“Poor”) stores tend to rely on more generic strengths, such as “minimalistic design” and “professional signage,” indicating limited differentiation.

2) Customer focus areas

“Signage focus” remains a primary area of attention across all performance levels. However, high-performing stores display greater diversity in focal points, such as “entrance area” and “seating area,” enhancing functionality and aesthetic appeal.

In contrast, lower-performing stores show limited engagement features, with customer attention concentrated on basic signage, suggesting opportunities for improvement in attracting and retaining customer interest.

3) Improvement suggestions

“Enhanced lighting” and “visibility improvement” are universal recommendations across all performance levels, reflecting the importance of clear and inviting storefront

visuals.

Lower-tier stores (“Poor” and “Fair”) are also advised to address issues like “curb appeal” and “window simplification.” High-performing stores (“Good” and “Excellent”), on the other hand, are encouraged to focus on refining details such as “promotional appeal” and “window organization” to maintain their edge.

These findings highlight how attention to design maturity—moving from basic functionality to refined presentation—correlates with perceived quality and customer engagement potential.

VI. LATENT DISPLAY TOPIC PREDICTIVE MODELS

After extracting the image keywords using three analytical methods, we developed label prediction models based on image features and two types of keywords. This approach involved defining label topics, preprocessing the data, extracting relevant features, training predictive models, and conducting model evaluation to determine the most effective methodologies for label prediction.

A. Label Topic Definition and Feature Extraction

The initial stage involved defining label topics by extracting and structuring image metadata. We employed Latent Dirichlet Allocation (LDA) (Jelodar, 2019) to extract topics from textual descriptions, determining the most coherent topic distributions. The optimal topic counts, determined based on coherence scores, were (5, 3, 4) for the initial suggestion keywords and (3, 6, 5) for the Neuron suggestion keywords.

Keywords were then vectorized into numerical representations to facilitate model training. Furthermore, topic consistency scores were computed to evaluate the stability of extracted themes. This ensured that the topics aligned with the primary visual and textual characteristics inherent in the dataset.

B. Predictive Model Development and Evaluation

1) Model training and performance evaluation

Three machine learning methods and cross-validation were applied to train to predict label topics and find the optimized parameters of models. The primary models tested included XGBoost (Ramraj, 2016), Random Forest (Speiser, 2019), and Logistic Regression (LaValley, 2008). Although the current state-of-the-art deep learning technology has certain advantages in accurately simulating the focus of the human eye, for small and medium-sized commercial stores, factors such as computing resources, data acquisition, interpretability, and deployability are more important. Therefore, using XGBoost, Random Forest, and Logistic Regression to construct label prediction on images processed by Neurons and related metadata is a more cost-effective option, which can provide actionable optimization suggestions under limited resources (Lundberg & Lee, 2017). The initial topic prediction model revealed overall poor predictive performance, with an Area Under the Curve (AUC) close to 0.5. Among the tested topics, Topic 3 achieved the highest AUC, with XGBoost emerging as the best-performing model (AUC = 0.5595). Topics 5 and 6 exhibited underwhelming performance across all models.

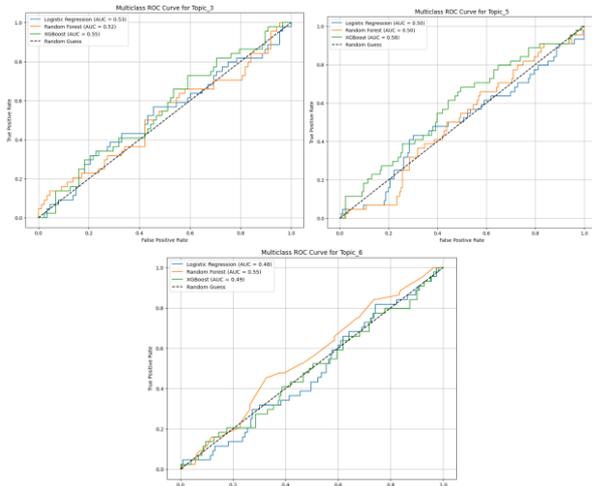


Fig. 13. ROC curve of three models for three latent display topics with initial keywords

Table 1. Initial (Prior) prediction accuracy and AUC for three models across three latent display topics

Initial (Prior) Prediction			
Topic	Model	Accuracy	AUC
Topic_3	Logistic Regression	0.38636364	0.53026617
Topic_3	Random Forest	0.34090909	0.5071641
Topic_3	XGBoost	0.38636364	0.55952044
Topic_5	Logistic Regression	0.15909091	0.49106739
Topic_5	Random Forest	0.11363636	0.50502208
Topic_5	XGBoost	0.27272727	0.58680168
Topic_6	Logistic Regression	0.11363636	0.45825516
Topic_6	Random Forest	0.20454545	0.5517891
Topic_6	XGBoost	0.15909091	0.47632112

Given these initial results, further refinements were made by incorporating additional features derived from neuron-based image assessments.

2) Neuron-processed feature analysis

To improve predictive accuracy, four neuron-derived features (Neuron_Focus, Neuron_Engagement, Clarity, and Cognitive Demand) and neuron heatmap image keywords were incorporated. To ensure the importance of the four neuron-driven features, we used mutual information scoring analysis (De Campos & Friedman, 2006) to assess their impact on model accuracy.

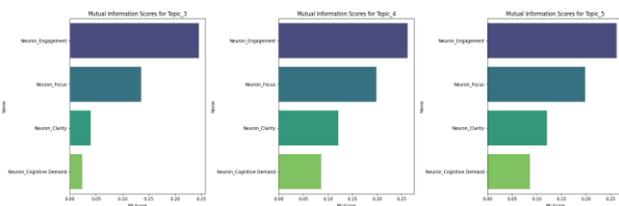


Fig. 14. Mutual information scores for three latent display topics.

Based on the mutual information scores, Neuron_Engagement emerged as the strongest predictor across three topics, followed by Neuron_Focus, whereas Neuron_Clarity and Neuron_Cognitive Demand demonstrated lower predictive significance. This suggests

that Neuron_Cognitive Demand and Clarity may have a lower impact on topic prediction, while Neuron_Engagement and Neuron_Focus may have a higher impact.

Given these findings, three comparative prediction runs were conducted: Using all four neuron-based features, excluding Clarity and Cognitive Demand, and excluding all four neuron-based features.

3) Comparative experiments with neuron features

Exclusion of All Four Neuron Features:

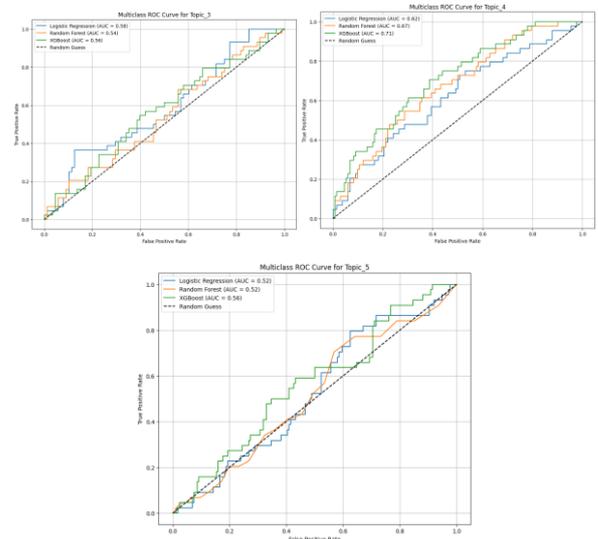


Fig. 15. ROC curve of three models with neuron keywords and without neuron features.

A slight improvement in accuracy and AUC was observed, yet the models still performed better than the initial predictions without neuron-based enhancements.

4) Exclusion of clarity & cognitive demand

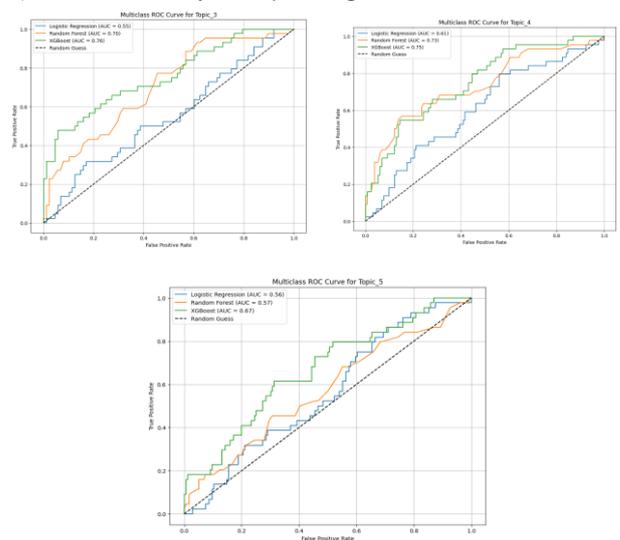


Fig. 16. ROC curve of three models with neuron keywords and two neuron features.

A significant increase in performance was noted, with XGBoost achieving an AUC of 0.7691 for Topic 3. At the same time, moderate performance was maintained for Topics 5 and 6, with XGBoost consistently outperforming other models.

5) Inclusion of all four neuron features

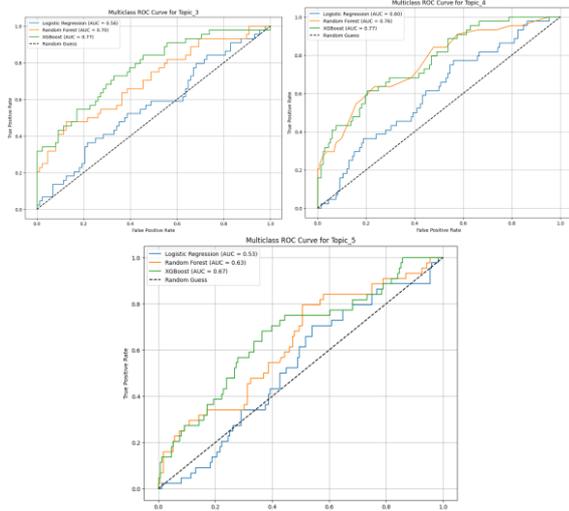


Fig. 17. ROC curve of three models with neuron keywords and four neuron features.

With all four neuron-based features added, the models reached the highest performance across all topics. Both Random Forest and XGBoost performed particularly well, with XGBoost achieving an AUC of 0.7832 for Topic 3. However, Logistic Regression continued to show relatively poor performance, with an average AUC of about 0.55 across all topics.

Table 2. Neuron (Post) prediction with three models among three latent display topics

Topic	Neuron Prediction	Without Four Neuron_*		Without Clarity & Demand		With Four Neuron_*	
		Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
Topic_3	Logistic Regression	0.386363 64	0.595 1401 6	0.363636 36	0.55807 451	0.386363 6364	0.5714 5373
	Random Forest	0.340909 09	0.535 1018 8	0.454545 45	0.69754 274	0.5 7051	0.7051 70813
	XGBoost	0.409090 91	0.573 2034 7	0.568181 82	0.76915 764	0.545454 5455	0.7832 226801
Topic_4	Logistic Regression	0.363636 36	0.498 939	0.363636 36	0.48048 082	0.363636 3636	0.5215 627584
	Random Forest	0.340909 09	0.632 4001 82	0.568181 332	0.64465 8182	0.568181 8182	0.6662 366154
	XGBoost	0.409090 91	0.676 5681 3	0.522727 27	0.73733 982	0.522727 2727	0.7079 241095
Topic_5	Logistic Regression	0.227272 73	0.511 2393 3	0.25	0.53644 471	0.136363 6364	0.5094 880884
	Random Forest	0.227272 73	0.495 7808 2	0.272727 27	0.54115 458	0.340909 0909	0.6175 341288
	XGBoost	0.227272 73	0.523 9212 1	0.363636 36	0.63544 44	0.340909 0909	0.6367 557465

Based on the label prediction results and mutual information score analysis, Neuron_Focus and Neuron_Engagement consistently demonstrated high predictive power, suggesting a strong association with consumer attention. In contrast, Cognitive Demand and Clarity contributed less to model performance, raising

questions about their relative informativeness.

One plausible explanation is that these features may be redundant with other high-information attributes, leading to reduced incremental value when included in the model. For instance, Cognitive Demand may overlap with Neuron_Engagement in capturing mental effort, while Clarity may already be reflected in visual contrast or structural organization features (Henderson & Hollingworth, 1999).

Additionally, Cognitive Demand and Clarity may encode a different dimension of attention allocation that is not fully captured in the existing dataset. Unlike Neuron_Focus and Neuron_Engagement, which directly correspond to gaze fixation and attentional intensity, Cognitive Demand reflects effortful processing, and Clarity relates to ease of perception—both of which may not be as directly correlated with immediate visual attention but could influence longer-term engagement and decision-making (Kümmeler *et al.*, 2016; Sweller, 1988). Furthermore, while the inclusion of neuron-based features led to notable improvements in model performance, particularly with XGBoost, our findings suggest that not all neuron-derived variables contribute equally. The differences in predictive strength could stem from how these features interact with other visual and contextual factors in the dataset. Future research could explore feature interaction effects and alternative representations to better capture these dimensions of attention allocation (Chen, 2016).

VII. CONCLUSION

A. Combined Approach

- (1) *Holistic Perspective:* While AI models like PaQ-2-PiQ and NIMA effectively evaluate aesthetic and perceptual quality, they do not explicitly map out *how* viewers distribute their attention.
- (2) *Attention Focus:* Neuromarketing outputs (particularly heatmaps) highlight zones that captivate the viewer’s gaze, enabling more targeted improvements—such as moving a sign to a more visually dominant spot or tweaking color palettes for better contrast.
- (3) *Accessibility for Small Businesses:* Traditional neuromarketing setups can be expensive. Neurons AI and similar platforms offer an affordable solution, scaling advanced attention insights for smaller enterprises.
- (4) *Actionable Optimization:* By uniting image-quality metrics with heatmap-based attention data, storefront owners can make informed, data-driven modifications. For instance, if signage is overshadowed in a heatmap, repositioning or enlarging it may significantly enhance visual prominence. For these insights to be widely applicable, especially for small businesses, there are practical challenges. Cost-effective and user-friendly platforms like Neurons AI provide an affordable solution for small enterprises, enabling them to leverage advanced attention insights without needing extensive technical expertise.

This combined approach ultimately empowers small businesses to optimize storefront designs based on both technical quality and predictive attention patterns, leading to more engaging and effective marketing displays.

B. Observations

- (1) Importance of Neuron Features: The inclusion of neuron-derived image assessments significantly enhanced predictive accuracy, particularly Neuron_Focus and Neuron_Engagement, which demonstrated strong contributions.
- (2) Model Performance Trends: XGBoost consistently outperformed other models, suggesting its suitability for this task. Random Forest and Logistic Regression exhibited moderate but suboptimal results.
- (3) Feature Sensitivity: Adding neuron-based features resulted in a remarkable increase in classification accuracy, underscoring their relevance in image label prediction.

VIII. RECOMMENDATION

Based on these findings, we propose the following recommendations for future research and practical implementations:

- (1) Leverage Neuron-Processed Images: Using neuron-processed image features is crucial for improving predictive accuracy and should be incorporated into future models.
- (2) Include Neuron_Focus and Neuron_Engagement Features: These features have demonstrated strong predictive value and should be prioritized in feature selection.
- (3) Employ Ensemble Methods for Complex Topics: Given the superior performance of XGBoost, ensemble learning approaches should be utilized, particularly for challenging topics such as Topic 5 and Topic 6.

This label prediction study demonstrates that incorporating neuron-based features enhances the accuracy of front door image label prediction models. By using machine learning techniques and feature engineering, we identified key variables that contribute to effective classification.

A promising avenue for our future research involves the development of adaptive AI systems that continuously learn from new data and consumer feedback. For example, reinforcement learning or A/B testing approaches could dynamically evaluate the effectiveness of visual changes. Additionally, future models could incorporate predictive elements regarding changes in foot traffic post-modification, making the findings even more actionable for small business owners.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

SL conducted the early stage image preprocessing, performed image scoring, and developed the manuscript outline; XY collected the initial image data, performed the data analysis and build up predictive models, and led the later stage writing and revision; VD served as the project sponsor and lab founder, providing strategic direction. RC carried out the post processing of neuron images. PS and YR developed methods for image based pattern extraction; AJ was responsible for code quality assurance and validation; all authors reviewed and approved the final version of the

manuscript.

REFERENCES

- Alvino, L., Pavone, L., Abhishta, A., & Robben, H. 2020. Picking your brains: Where and how neuroscience tools can enhance marketing research. *Frontiers in Neuroscience*, 14, 577666.
- Bitner, M. J. 1992. Servicescapes: The impact of physical surroundings on customers and employees. *Journal of Marketing*, 56(2): 57–71.
- Chebat, J. C., G elinas-Chebat, C., & Therrien, K. 2005. Lost in a mall, the effects of gender, familiarity with the shopping mall, and the shopping values on shoppers' wayfinding processes. *Journal of Business Research*, 58(11): 1590–1598.
- Chen, T. 2016. XGBoost: A Scalable Tree Boosting System. Cornell University.
- Clement, J., Kristensen, T., & Gr nhaug, K. 2013. Understanding consumers' in-store visual perception: The influence of package design features on visual attention. *Journal of Retailing and Consumer Services*, 20(2): 234–239.
- Das, G., & Varshneya, G. 2017. Consumer emotions: Determinants and outcomes in a shopping mall. *Journal of Retailing and Consumer Services*, 38: 177–185.
- Daugherty, P. R., Wilson, H. J., & Chowdhury, R. 2018. Using artificial intelligence to promote diversity. *MIT Sloan Management Review*.
- De Campos, L. M., & Friedman, N. 2006. A scoring function for learning Bayesian networks based on mutual information and conditional independence tests. *Journal of Machine Learning Research*, 7(10).
- Dimpfel, W. 2015. Neuromarketing: Neurocode-tracking in combination with eye-tracking for quantitative objective assessment of TV commercials. *Journal of Behavioral and Brain Science*, 5(04): 137.
- Gill, R., & Singh, J. 2020. A review of neuromarketing techniques and emotion analysis classifiers for visual-emotion mining. *Proceedings of 2020 9th International Conference System Modeling and Advancement in Research Trends (SMART)*: 103–108, IEEE.
- Grewal, D., Roggeveen, A. L., & Nordf alt, J. 2017. The future of retailing. *Journal of Retailing*, 93(1): 1–6.
- Henderson, J. M., & Hollingworth, A. 1999. High-level scene perception. *Annual Review of Psychology*, 50(1): 243–271.
- Huang, Z., & Benyoucef, M. 2013. From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications*, 12(4): 246–259.
- Huang, M. H., & Rust, R. T. 2021. A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1): 30–50.
- Jelodar, H., Wang, Y., Yuan, C., Feng, X., Jiang, X., Li, Y., & Zhao, L. 2019. Latent Dirichlet Allocation (LDA) and topic modeling: models, applications, a survey. *Multimedia Tools and Applications*, 78(11): 15169–15211.
- Kerfoot, S., Davies, B., & Ward, P. 2003. Visual merchandising and the creation of discernible retail brands. *International Journal of Retail & Distribution Management*, 31(3): 143–152.
- K ummerer, M., Wallis, T. S., & Bethge, M. 2016. DeepGaze II: Reading fixations from deep features trained on object recognition. arXiv preprint arXiv:1610.01563.
- LaValley, M. P. 2008. Logistic regression. *Circulation*, 117(18): 2395–2399.
- Levy, M., Weitz, B. A., & Grewal, D. 2019. *Retailing Management*, 10th. edit. ed.
- Lundberg, S. M., & Lee, S. I. 2017. A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30.
- Metropolitan Transportation Commission. San Francisco Bay Region incorporated cities and towns. [Online]. Available: <https://opendata.mtc.ca.gov/datasets/MTC::san-francisco-bay-region-incorporated-cities-and-towns-1>.
- Milosavljevic, M., Koch, C., & Rangel, A. 2011. Consumers can make decisions in as little as a third of a second. *Judgment and Decision*

Making, 6(6): 520–530.

- Plassmann, H., Ramsøy, T. Z., & Milosavljevic, M. 2012. Branding the brain: A critical review and outlook. *Journal of Consumer Psychology*, 22(1): 18–36.
- Parsa, H. G., Lord, K. R., Putrevu, S., & Kreeger, J. 2015. Corporate social and environmental responsibility in services: Will consumers pay for it? *Journal of Retailing and Consumer Services*, 22: 250–260.
- Pfeiffer, T., & Memili, C. 2016. Model-based real-time visualization of realistic three-dimensional heat maps for mobile eye tracking and eye tracking in virtual reality. *Proceedings of the Ninth Biennial ACM Symposium on Eye Tracking Research & Applications*: 95–102.
- Quartier, K., Vanrie, J., & Van Cleempoel, K. 2014. As real as it gets: What role does lighting have on consumer's perception of atmosphere, emotions and behaviour? *Journal of Environmental Psychology*, 39: 32–39.
- Ramraj, S., Uzir, N., Sunil, R., & Banerjee, S. 2016. Experimenting XGBoost algorithm for prediction and classification of different datasets. *International Journal of Control Theory and Applications*, 9(40): 651–662.
- Rawnaque, F. S., Rahman, K. M., Anwar, S. F., Vaidyanathan, R., Chau, T., Sarker, F., & Mamun, K. A. A. 2020. Technological advancements and opportunities in Neuromarketing: A systematic review. *Brain Informatics*, 7(1): 10.
- Speiser, J. L., Miller, M. E., Tooze, J., & Ip, E. 2019. A comparison of random forest variable selection methods for classification prediction modeling. *Expert Systems with Applications*, 134: 93–101.
- Sweller, J. 1988. Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2): 257–285.
- Talebi, H., & Milanfar, P. 2018. NIMA: Neural image assessment. *IEEE Transactions on Image Processing*, 27(8): 3998–4011.
- Ungureanu, F., Lupu, R. G., Cadar, A., & Prodan, A. 2017. Neuromarketing and visual attention study using eye tracking techniques. *Proceedings of 2017 21st International Conference on System Theory, Control and Computing (ICSTCC)*: 553–557. IEEE.
- Wedel, M., & Pieters, R. 2008. Eye tracking for visual marketing. *Foundations and Trends® in Marketing*, 1(4): 231–320.
- Wedel, M., & Pieters, R. 2015. The buffer effect: The role of color when advertising exposures are brief and blurred. *Marketing Science*, 34(1): 134–143.
- Ying, Z., Niu, H., Gupta, P., Mahajan, D., Ghadiyaram, D., & Bovik, A. 2020. From patches to pictures (PaQ-2-PiQ): Mapping the perceptual space of picture quality. *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*: 3575–3585.

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