https://doi.org/10.31489/2025Ec2/4-16

JEL M31 Received: 28.12.2024. | Accepted: 03.04.2025.

ORIGINAL RESEARCH

Neuromarketing Insights: Using Eye-Tracking and Machine Learning to Understand Consumer Preferences for University Promotional Products

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Abstract

This research applies neuromarketing approaches along with traditional marketing tool like self-report to study how design factors, such as visual appeal, quality and pricing, affect consumer engagement with promotional products at Almaty Management University. It explores how eye-tracking measures affect consumer preferences and how machine learning can be used to predict consumer behavior. 16 university students and young professionals participated in this quantitative study and interacted with a range of promotional items, including clothing, stationery and dishware. Gaze patterns and fixation durations were recorded using eye-tracker technology, and data including survey results were analyzed using machine learning model such as random forest classifiers to find patterns in consumer preferences. The results suggest that visually appealing designs increase consumer attraction and perceived attractiveness, especially in clothing. Eye-tracking metrics, such as size (cm^2) and dwell time, were strongly correlated with attractiveness ratings and were identified by machine learning models as key features in predicting. The study emphasizes the importance of visual appealing products in increasing consumer engagement and brand loyalty. This study offers insightful information about how eye-tracking and machine learning can be used to predict consumer behavior in the context of promotional products. The results highlight how important visual design is in attracting consumers, by offering practical implications for marketers to improve promotional products.

Keywords: Neuromarketing, Eye-tracking technology, Consumer behavior, Promotional products, Visual engagement, Machine learning

Introduction

Understanding consumer behavior has turned into a necessary element for more successful marketing strategies, most particularly in today's competitive marketplace, in which consumers are bombarded constantly with visual stimuli. Brands must seek methods to capture sufficient attention. Also, brands should sustain attention in an environment that is flooded with advertisements. Promotional products, for example stationery or clothing, are marketing tools which strongly connect with consumers and sway their decision-making. For higher education institutions such as Almaty Management University, effectively engaging many students and young professionals through various promotional products can greatly help increase such brand awareness and loyalty.

Neuromarketing, integrating certain principles of neuroscience with marketing strategies, offers definite tools for uncovering the specific drivers behind consumer behavior. Eye-tracking technology, in particular, allows data collection in real-time on how consumers interact visually with promotional products. It captures attention metrics such as where consumers look, how long they focus on specific visual elements, as well as how their gaze shifts during product interaction (Bulling & Wedel, 2019). This said ability for measurement of visual salience — the natural ability of certain design elements for attraction of attention — can give marketers actionable understandings into consumer preferences and decision-making processes.

The research on the use of eye-tracking technology for university promotional materials, especially in dynamic, real-world contexts, is still lacking, despite the growing interest in neuromarketing. Few studies have combined survey data with eye-tracking measures to analyze consumer involvement in dynamic situations, despite the fact that the majority of current research focuses on static areas of interest (AOIs) and screen-based devices (Xie et al., 2024). By integrating survey data, eye-tracking devices, and machine learning algorithms, this study aims to close that knowledge gap and provide a more thorough picture of how customers interact with Almaty Management University's promotional goods.

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The study tackles the research problem of requiring a more profound understanding of how consumers interact with promotional products and the elements that affect their decision-making processes. Neuromarketing instruments, particularly eye-tracking technology, have demonstrated effectiveness in advertising and retail. Nonetheless, their application in the higher education field, particularly for university marketing items, has not been extensively explored. This research intends to fill this gap by integrating survey data with eye-tracking metrics and machine learning models to forecast consumer preferences and behavior.

The main objective of our research is to study how certain characteristics of promotional products affect consumer perception. To achieve this goal, the following objectives were set:

1. To assess consumer attitudes towards various categories of promotional products and product characteristics (e.g., price, quality, etc.) using a survey method;
2. To study gaze patterns obtained using an eye-tracker;
3. To identify the key features of the promotional products that have a high correlation with the perceived attractiveness of products and show statistical significance in predicting consumer behavior.

The results of our study revealed valuable insights for future researches, and also offered practically applicable insights for improving the marketing strategy of universities. Their implementation can help improve promotional products that can more effectively attract the target audience and increase the perceived attractiveness of goods. In a theoretical perspective, our work makes a modest contribution to the growing body of literature in the field of neuromarketing by expanding our vision and understanding of the unconscious processes occurring in the “black box” of consumers, that influence their decision-making process.

To achieve these objectives, our study used a quantitative approach that integrated survey results, machine learning models, and eye-tracking technology. Eye-tracker explored areas of interest (AOI) by assessing fixation-based metrics and saccade-based metrics, identifying design elements that aroused the greatest interest among respondents. Survey data, in turn, answer the question “why?”, thereby complementing the eye-tracker results and providing context for the obtained metrics. The use of machine learning algorithms such as random forest and principal component analysis (PCA) make it possible to predict consumer behavior, in particular, the perceived attractiveness of promotional products.

Literature Review

In today’s visually overwhelming market, understanding consumer behavior is critical for developing effective marketing strategies. Neuromarketing, which combine neuroscience with marketing practices, offers valuable tools to study subconscious consumer behavior. Among these tools, eye-tracking has become one of the essential methods, which is able to examine how visual stimuli impact consumer perception and decision-making. This literature review explores the integration of eye-tracking technology with machine learning models to better understand visual attention and its impact on consumer behavior. In particular, it aims to investigate the role of visual stimuli, such as size and layout, in consumer engagement with promotional products. The review will address key aspects, such as the role of neuromarketing, the application of eye-tracking technology, visual attention, and machine learning integration.

Neuromarketing and Eye-Tracking Technology

Neuromarketing uses neuroscience approach to reveal consumer’s physiological and cognitive responses to marketing stimuli. By using neuroimaging and biometric methods, neuromarketing captures real-time consumer reactions, offering insights into subconscious decision-making processes that traditional research methods often overlook. Aldayel et al. (2020) note that this approach provides a more precise understanding of consumer preferences. Using physiological metrics, neuromarketing identifies factors that capture consumer attention and drive decision-making, thereby helping to improve product positioning and marketing effectiveness.

Within this context, eye-tracking technology has become one of the main tools of neuromarketing, which measure physiological responses of consumers. It examines how consumers visually engage with marketing stimuli. By tracking eye movements, fixation durations, and gaze patterns, researchers can identify which elements of a product or advertisement draw consumer attention. These metrics offer valuable insights into consumer perception and decision-making (Martinovici et al., 2022).

Olarte (2021) highlights the importance of using eye-tracking beyond controlled laboratory settings, emphasizing its utility in real-world scenarios involving physical objects. The study also underscores how design features such as layout, background, and object size can significantly influence attention-related metrics like time to first fixation and dwell time. Similarly, Xie et al. (2024) demonstrate that such visual design elements have a measurable effect on consumer decision-making processes.

These findings support the present study's use of tangible promotional products in a naturalistic display and justify the inclusion of layout and size as key design variables. Furthermore, recent research suggests that neuromarketing techniques can also inform branding strategies in educational settings. For instance, student-oriented promotional design may benefit from identifying which visual features increase brand recall and engagement in high-stimulus environments like university campuses (Mashrur et al., 2023).

Visual Attention and Consumer Behavior

Visual attention is vital in consumer decision-making process. The way how consumers engage with visual elements — what they focus on and for how long — directly impacts their perceptions and purchasing decisions. Research by Kim and Kim (2024) and Pieters and Wedel (2004) shows that attention is shaped both by bottom-up factors (e.g., color, size) and top-down factors (e.g., expectations, goals). This dual influence is particularly important in marketing contexts, where design features must both stand out and align with consumer interests. Metrics such as fixation count, dwell time, and time to first fixation are considered reliable indicators of engagement. Gao and Kasneci (2022) show that higher fixation counts and longer dwell times often correlate with stronger consumer interest. These insights have practical implications for optimizing the design of promotional materials to better capture and sustain attention. Šola et al. (2025) reinforce the role of visual structure in shaping user attention. Their study on reader engagement with digital magazine content found that layout composition, spatial organization and content density significantly influence attention patterns and cognitive processing. Although the context differs, the principle — that design layout directly impacts attention — is relevant to optimizing the appeal and clarity of promotional products.

Machine Learning in Eye-Tracking Research

The combination of machine learning and eye-tracking technology significantly improves the prediction of consumer behavior. Gao and Kasneci (2022) note that machine learning algorithms can reveal patterns in eye-tracking data, which improves the accuracy of predictions regarding consumer preferences and purchasing intent. By analyzing factors such as fixation duration and areas of interest, machine learning models can refine predictions and optimize marketing approaches.

Juárez-Varón et al. (2020) applied Random Forest and clustering models to eye-tracking data in a product packaging study. Their results highlight the predictive value of AOIs, fixation counts, and revisit patterns in determining which design elements attract or lose consumer interest. These methodological parallels directly support this study's use of Random Forest Regressor and Hierarchical Clustering to analyze how consumers interact with university-branded promotional items. The focus on design elements such as layout and size further align with their findings, where visual characteristics were shown to significantly influence consumer preference. In addition, machine learning enables marketers to automate prediction of consumer engagement without manual feature engineering. Techniques like RETINA, a deep learning model described by Unger et al. (2023), suggest that attention trajectories — the order and time spent on different visual elements — can reveal decision-making intent with high predictive power. Though our study uses more interpretable models, these findings underscore the growing potential of combining physiological data with algorithmic interpretation to inform strategic marketing.

Gaps in the Literature

The design of promotional products can directly benefit from the insights gained from machine learning and neuromarketing. Optimizing the visual layout and positioning important information in high-attention zones can greatly boost product engagement, as previous study indicates (Goldberg et al., 2021). These high-impact locations are identified with the aid of eye-tracking study insights. Design elements like color, form, and testimonial usage can be adapted to create appeal and credibility in educational branding environments. Emotionally resonant colors and endorsements (such as alumni quotations) improve perceived credibility and connectedness, according to Mashrur et al. (2023). This literature confirms the significance of design detail in promotional efficacy, even if our study does not specifically evaluate emotional responses.

In spite of significant advancements in eye-tracking studies, there are still some gaps in the thorough understanding of consumer behavior. Numerous current studies center on individual eye-tracking metrics, like fixation duration, without examining how other eye-tracking metrics interplay to affect decision-making. Xie et al. (2024) emphasizes the need for a more cohesive method for eye-tracking that takes into account various data points. Additionally, much of the current research has concentrated on static areas of interest (AOIs) or screen-oriented devices in controlled laboratory settings, which might not entirely represent actual consumer behavior in the real world. In this context, portable eye-trackers provide more natural and flexible measurements along with promising avenues for future research.

This current gap emphasizes the need for studies that examine the application of eye-tracking tools in practical settings, such as mobile devices or retail spaces. The current body of research reveals a complicated connection between visual attention and consumer behavior, with eye-tracking technology offering crucial insights into consumer interactions with products. Essential metrics, including fixation time and gaze frequency, are linked to heightened consumer interaction and can act as signs of buying intentions. Combining eye-tracking data with machine learning models can improve the ability to forecast consumer behaviors and refine marketing approaches.

This literature review has explored the function of eye-tracking technology in neuromarketing, emphasizing its capability to monitor consumer attention and foresee behavior. By combining eye-tracking with machine learning techniques, marketers can obtain enhanced understanding of consumer decision-making processes. The review emphasizes the significance of visual cues in shaping consumer perceptions and choices, establishing a solid basis for this research.

Methods

This research investigates consumer behavior in the context of promotional products at Almaty Management University, using a neuromarketing framework that combines eye-tracking technology with machine learning techniques. By analyzing consumer engagement through visual attention metrics, the study aims to identify the key factors which impact consumers' decision-making. The study aims to receive practically useful results and address important questions related to consumer preferences, eye-tracking metrics and design features of the promotional products such as layout and size.

Research Questions:

– How do design attributes (such as size and layout) impact consumer engagement with promotional products at Almaty Management University?

– How do eye-tracking metrics correlate with consumers' perceived attractiveness towards promotional products?

– How well machine learning models can predict consumer engagement and perceived attractiveness based on eye-tracking metrics?

Hypothesis:

It is hypothesized that visually appealing design elements, like size and layout, will have a positive impact on consumer engagement and perceived attraction of promotional products of Almaty Management University. Specially, products which have larger visual features and more visually appealing designs will attract more attention of consumers, which will lead to higher levels of engagement, and more likely to be rated as more attractive.

Also, it is expected that the integration of machine learning models **(**such as Random Forest and Hierarchical Clustering) with eye-tracking data will be able to improve the prediction of consumer preferences. By analyzing eye-tracking metrics such as fixation duration and gaze frequency, machine learning techniques will provide deeper insights into the relationship between visual stimuli and consumer behavior, which can offer more accurate and deeper understanding of consumer decision-making processes.

Participant Recruitment

The study uses a quantitative research method, using eye-tracking technology to collect data on participants' visual interactions with Almaty Management University's promotional products. The sample consisted of 16 participants (8 female, 8 male), aged 18–31. They were senior undergraduate students and early-career university employees, collectively defined as young professionals. This demographic was selected based on its strong alignment with the target audience of university promotional materials and its active engagement in both the university's social and physical environments. Recent literature supports the relevance of young professionals in branding research. Macalik (2023) emphasizes that young professionals, such as final-year students and early-stage employees, are increasingly attuned to branding as part of their personal and professional development. They demonstrate high sensitivity to visual identity, design cues, and messaging due to their active roles in social media, peer influence, and institutional representation. These individuals act as informal brand ambassadors, sharing experiences both online and offline, and are therefore highly relevant for testing responses to branded content in naturalistic settings. Their entrepreneurial mindset and openness to innovation further justify their inclusion in neuromarketing studies, where emotional and cognitive responses to design are key evaluation points. Moreover, this group's routine exposure to university-branded materials — through events, onboarding processes, campus environments, and digital platforms — ensures high ecological validity. According to ESOMAR guidelines, researchers are expected to ensure that their sample sources are appropriate for the research purpose and representative of the relevant population. This implies that selecting participants who reflect the natural target audience of a product or brand enhances the relevance and interpretability of the results (ESOMAR, n.d.). While the sample size is below standard statistical thresholds, this sample aligns with neuromarketing research practices where smaller, targeted samples are common due to the consistency of physiological responses (Kazybayeva, 2022). Vozzi et al. (2021) found that even with as few as 16 participants, meaningful and interpretable results could be obtained, particularly when analyzing physiological metrics like EEG, eye movements, or skin conductance. In their neuromarketing case study, they demonstrated that although data variability increases as sample size decreases, subgroups of 16 participants still produced moderately strong correlations with the full-sample results. However, it is recommended for future researches to include more participants in order to improve representativeness of the study.

Equipment and Materials

Eye-tracking data was collected using the Tobii Glasses 2 device, a highly accurate portable neuromarketing tool, which is often used in neuromarketing researches. This device tracks eye movements, providing metrics such as fixation duration, saccades' counts, and areas of interest (AOIs) and etc. These metrics are important for understanding how visual elements of promotional products capture consumer's attention (Pieters & Wedel, 2004).

The promotional products which were used in this study were categorized into three main groups**:** Clothing (T-shirts, Sweatshirts), Stationery (Notebooks, Diaries), and Dishware (Mugs, Bottles, Thermoses). Hierarchical Clustering analysis later confirmed that this categorization was effective for comparing eye-tracking metrics across different groups.

Procedure

The experiment was conducted in a quiet study room at the university. A section of the room was partitioned off by a curtain to conceal the stimuli until participants were ready. The product display was designed to replicate a real-life campus environment, mimicking the university's entrance hall where such items are commonly exhibited. Branded products, such as T-shirts, mugs, thermoses, stickers, diaries, and notebooks and etc., were arranged on a large table in natural positions to create a familiar, ecologically valid context. After participants were informed about the study's aims, each of them went through calibration process to ensure that eye-tracking process will be highly-precise. Then, participants entered the space one at a time, with sufficient time intervals to prevent influence from prior sessions, especially since a few participants verbally commented during their interaction despite not being prompted to do so. Once inside, participants were left completely alone to interact with the items. This was done deliberately to minimize the observer effect and allow for a more authentic, self-paced experience. Instructions were minimal; participants were told to interact with the items as they would naturally. They were free to touch, pick up, or simply look at the products, with no imposed time limits. On average, they spent about 1,5 minutes exploring the display, though some remained longer and others less, depending on personal interest. The naturalistic, unmonitored setting was key to maintaining ecological validity and reducing artificial behavioral cues.

After interacting with promotional products, participants were asked to complete a survey in order to have a deeper understanding of their preferences for the promotional products and the importance of attributes like Quality**,** Design Appeal**,** Price**,** and Functionality. This combination of subjective responses and objective eye-tracking data regarding respondents' physiological responses provided a broader understanding of consumer engagement.

Data Collection and Analysis

Key eye-tracking metrics were analyzed to define consumer engagement:

- AOI Metrics: Duration of gaze on certain areas of interest.
- Fixation-based Metrics: Number of fixations and their duration.
- Saccade-based Metrics: Number and amplitude of quick eye movements between fixations.

Survey responses were combined with eye-tracking data to have a broader understanding of consumer preferences and define consumer behavior patterns. The data analysis was proceeded using machine learning models such as non-linear regression (Random Forest Regressor) and cluster analysis **(**Hierarchical Clustering**)** to define patterns and correlations between physiological responses and self-report results.

Machine Learning Models

1. Random Forest:

The Random Forest Regressor was designed to define the key features which impact consumer attraction. The model focused on eye-tracking metrics like size (cm²) and dwell time. The quality of the model's performance was evaluated using Mean Squared Error (MSE) and R^2 to ensure its accuracy in predicting.

2. Hierarchical Clustering:

This model divided promotional products into certain categories according to the engagement metrics which were obtained from eye-tracker. The clustering algorithm used Ward's method to minimize variance and identify patterns in consumers' attraction across different product categories. This helped to define the product groups which captured the most attention.

The methodology combines self-report and eye-tracking technology with machine learning to create a comprehensive model for understanding consumer engagement and behavior.

Results

Survey Results

Key findings of survey show strong preferences for clothing products and price sensitivity.

1. Attractiveness of Promotional Products

The survey analyzed consumers' preference of 3 promotional product categories, revealing following results:

– Clothing: 81 % of respondents showed a preference for clothing items, highlighting their importance as promotional products.

– Stationery: 9.5 % of respondents expressed attraction towards stationery, showing a lower level of attraction in this category.

– Dishware: 9.5 % of respondents also preferred dishware, with the same level of perceived attraction as in stationery.

2. Importance of Product Characteristics

Respondents rated the importance of various product characteristics on a scale from 1 to 5:

Table 1. Importance of Product Characteristics as Rated by Respondents

Characteristic	Average Rating
Quality	3.57
Attractiveness of Design	4.33
Price	4.43
Functionality/Practicality	3.86
Overall Average	**4.05**

Note: Compiled by the authors based on research.

These findings show that while quality (3,57) is valued, the attractiveness of design (4,33) is more important for respondents. Additionally, the affordability of price was rated as the most important characteristic (4,43) for the respondents in decision-making process (see Table 1).

Eye-Tracking Metrics

Eye-tracking tool provided results which consist of several metrics, which can be divided into three main categories: AOI-based metrics, fixation-based metrics and saccade-based metrics.

AOI-Based Metrics

– AOI Duration (%): This metric shows the percentage of respondents' total viewing time spent on certain areas of interest (AOI). Higher values mean that the visual features within the AOI attract more attention.

– Size (%): This metric represents the relative size of the AOI as a percentage, showing how much of the screen area occupied by the object. Larger size (%) may attract more attention because of its visual prominence.

– Fixation-Based Metrics

– Fixation Count: This metric shows the number of times when the respondent's gaze was fixed on a certain AOI. More fixations typically mean stronger interest or need for closer inspection.

– TTFF AOI (ms): The Time To First Fixation (TTFF) measures how quickly the viewer's gaze is attracted to a specific AOI. Shorter times usually indicate quicker attraction.

– Dwell Time (ms): This represents the total time spent looking at an AOI. Longer dwell times suggest increased interest or difficulty in processing information.

– First Fixation Duration (ms): This metric measures the time spent on the first fixation. Longer first fixations typically reflect stronger initial attraction or interest.

– Saccade-Based Metrics

– Saccade Count: This metric refers to the number of quick eye movements (saccades) made between different AOIs. Higher saccade counts generally suggest active exploration of the visual content.

– Amplitude (deg): This refers to the angular distance the eyes move between fixations. Larger amplitudes indicate a more active exploration of the content.

As shown in Table 2, clothing consistently outperformed both dishware and stationery in terms of attention metrics, indicating that clothing is the most visually appealing category in Almaty Management University's promotional products. This supports the idea that aesthetically pleasing products, particularly those with larger visual features, are more likely to engage consumers (Janiszewski, 1998). Dishware and stationery, though still attracting some attention, did not capture consumer interest as strongly as the clothing items.

Table 2. Eye-Tracking Metrics by Category

Metric	Clothing	Dishware	Stationery
AOI Duration (%)	100	100	100
Size (%)	4.65	1.80	2.47
Fixation Count	2.525	1.4	1.77
TTFF AOI (ms)	958.45	2965.6	2669.77
Dwell Time (ms)	355.85	268	221.67
First Fixation Duration (ms)	166.25	128	133.33
Saccade Count	4.23	1.7	2.43
Amplitude (deg)	4.07	3.90	3.37
Note: Compiled by the authors based on research.			

These findings align with survey results, which also highlighted clothing as the most attractive promotional product category.

Machine Learning Model Results

1. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a technique used to simplify complex data while keeping only key information. In this study, this method was applied to the eye-tracking data to replace the traditional heatmap, offering a more accurate measure of consumer engagement (see Fig. 1). By analyzing eye-tracking metrics like AOI duration (%), size (%), dwell time (ms), and saccade count, PCA reduced the data and provided Overall Intensity score for each product, which reflects consumer attraction levels.

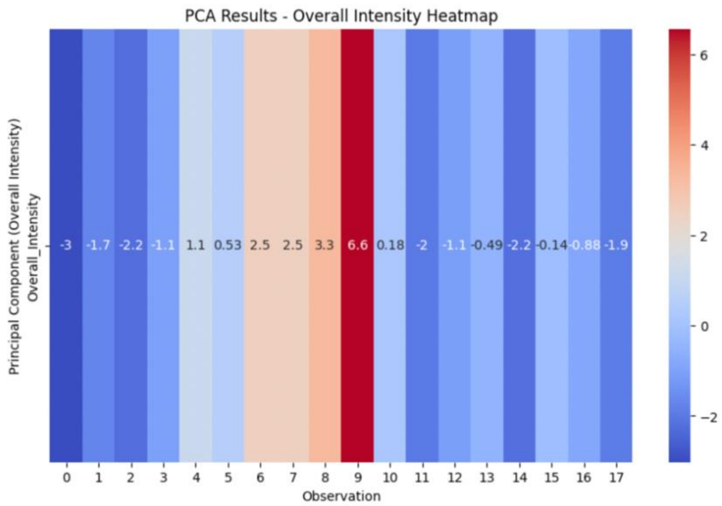

Figure 1: Heatmap of PCA Results for Overall Intensity of Promotional Products

Note: The results were obtained using Python, with data processed through a PCA (Principal Component Analysis) algorithm, and visualized accordingly.

The Overall Intensity scores were categorized as low, medium, or high based on their value. Scores below –1.5 were identified as low, between –1.5 and 2.5 medium, and above 2.5 high. This categorization helped to define which products attract more attention. Table 3 shows the Overall Intensity scores and their categorization based on PCA results.

Table 3. Overall Intensity and Categorization of Promotional Products Based on PCA Results

Number	Object Name	Object Color	Object Category	Overall Intensity	Intensity Category
0	Thermocup	White	Dishware	–3.02	Low
1	Thermos	Dark Blue	Dishware	–1.72	Low
2	Thermal Bottle	Gray	Dishware	–2.24	Low
3	Mug	Dark Blue	Dishware	–1.07	Medium
4	T-shirt	Dark Blue	Clothing	1.14	High
5	T-shirt	White	Clothing	0.53	High
6	T-shirt	Black	Clothing	2.54	High
7	Bomber	Red	Clothing	2.51	High
8	Sweatshirt	Dark Blue	Clothing	3.33	High
9	Sweatshirt	Black	Clothing	6.57	High
10	Sticker	Light Blue	Stationery	0.18	Medium
11	Sticker	Dark Blue	Stationery	–1.98	Low
12	Sticker Mini	White	Stationery	–1.10	Medium
13	Diary	Gray	Stationery	–0.49	Medium
14	Diary	Dark Blue	Stationery	–2.20	Low
15	Diary	Red	Stationery	–0.14	Medium
16	Copybook	White	Stationery	–0.88	Medium
17	Copybook	Gray	Stationery	–1.94	Low
Note: Compiled by the authors based on research.					

The PCA results showed that clothing products, such as the T-shirt (Black) and Sweatshirt (Dark Blue), had higher Overall Intensity scores, showing higher consumer engagement. These items also had larger size (%) metric, suggesting that products with larger visual features are more likely to attract consumers' attention. On the contrary, dishware and stationery category products with smaller size percentages received low or medium intensity scores.

2. Hierarchical Clustering Analysis

Hierarchical Clustering was used to categorize promotional products based on their eye-tracking metrics, in order to confirm the initial categorization of Clothing, Dishware, and Stationery product groups. This analysis aimed to identify distinct engagement patterns within these product categories. The ML model was applied using the fcluster() function from scipy.cluster.hierarchy, which clustered the products into three groups based on the similarities in their engagement metrics obtained from eye-tracker.

Interestingly, the application of the Machine Learning model showed the same classification of products into three clusters, as in the original categories of Clothing, Dishware, and Stationery (see Fig. 2). This alignment not only validates the initial product categorization but also highlights the effectiveness of the eye-tracking metrics. These metrics show that visually engaging products, especially in the clothing category, attract more consumer attention. The fact that these eye-tracking results align with the logical categorization of products confirms that products within the same category provoke similar physiological responses, highlighting the consistency of consumer engagement across different product types.

```
Objects in Cluster 1:
       Color Category  AO1 duration (msAO1 duration (ms)  Size (%)
4  dark-blue  clothes                            4488.7       9.9
5      white  clothes                            4488.7      11.5
6      black  clothes                            4488.7      14.4
7        red  clothes                           11407.9       8.6
8  dark-blue  clothes                           11407.9      11.5
9      black  clothes                           11407.9      19.7

Objects in Cluster 2:
       Color  Category  AO1 duration (msAO1 duration (ms)  Size (%)
0      white  dishware                           16698.5       1.2
1  dark-blue  dishware                           16698.5       1.4
2       gray  dishware                           16698.5       1.3
3  dark-blue  dishware                           16698.5       1.0

Objects in Cluster 3:
         Color         Category  AO1 duration (msAO1 duration (ms)  Size (%)
10  light-blue  office supplies                            4410.0       4.2
11   dark-blue  office supplies                            4410.0       4.3
12       white  office supplies                            4410.0       2.5
13        gray  office supplies                            8410.1       3.3
14   dark-blue  office supplies                            8410.1       3.3
15         red  office supplies                            8410.1       3.7
16       white  office supplies                            4343.1       6.6
17        gray  office supplies                            4343.1       2.9
```

Figure 2. Hierarchical Clustering Results for Promotional Products

Note: The clustering results were obtained using Python and visualized with the help of a hierarchical clustering algorithm.

Using key eye-tracking metrics such as AOI duration, Fixation count, and Dwell time, the products were grouped into three clusters:

Cluster 1: This cluster, consisting of clothing items, was characterized by high engagement. Products like t-shirts, sweatshirts, and bombers with larger visual features attracted higher levels of consumer attention. These products also showed high Fixation counts and Dwell time, indicating that clothing items not only captured attention but held it for longer time.

Cluster 2: Consisting of dishware items, this cluster showed medium level of engagement. While Amplitude (deg) and Saccade counts were not as high as in Cluster 1, products like thermocup and thermal bottles still drew notable level of attention. The TTFF AOI (Time to First Fixation) and Fixation counts in this cluster showed a reasonable level of engagement, although lower compared to clothing items.

Cluster 3: This cluster encompassed stationery, which attracted the least attention from respondents. Dwell time and Fixation count were noticeably lower, with items like diaries and copybooks receiving less engagement. Interestingly, despite the overall lower attention metrics, some stationery like copybooks showed moderate engagement in specific metric such as Saccade count, suggesting that they were occasionally revisited for closer inspection.

This analysis not only confirmed the initial categorization but also provided deeper insights into the engagement levels across these groups. The precise alignment of the ML clustering results with the original categories underscores the effectiveness of both the experiment's design and the application of Machine Learning in deriving meaningful insights.

3. Random Forest Regressor for Attractiveness Prediction

A Random Forest Regressor model was employed to predict the attractiveness ratings of promotional products based on a range of eye-tracking and product-related features. As an ensemble learning method, Random Forest constructs multiple decision trees to enhance prediction accuracy and mitigate overfitting, making it particularly suitable for this analysis. The model was trained using features such as AOI duration, product size, dwell time, and additional metrics to predict attractiveness ratings, which were derived from survey responses. The dataset was divided into 70 % for training and 30 % for testing. The model's performance was then assessed through the Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2 Score.

Model Evaluation Metrics

– Mean Absolute Error (MAE): 2.47, showing that, the model's predictions differ from the actual ratings, on average, by 2.47 points.

– Mean Squared Error (MSE): 7.28, it measures the average of the squared differences between the predicted and actual values, showing the differences between them.

– R^2 Score: 0.57, suggesting that the model accounts for approximately 57 % of the variance in attractiveness ratings. While not perfect, this result signifies that the model captures a substantial portion of the relationship between eye-tracking features and perceived product attractiveness.

The Random Forest model's evaluation metrics provide a further understanding of how well these visual and engagement features predict consumer preferences.

Feature Importance

Feature importance in machine learning indicates which factors are most influential in predicting a target variable — in this case, the attractiveness ratings. In the Random Forest model, each feature is assigned an importance score, showing how much it contributes to the model's predictions. A higher score means a feature plays a bigger role in determining attractiveness. Feature importance analysis revealed the following key drivers:

1. Size (cm²): 23.47 %, indicating that larger products are perceived as more attractive.
2. Dwell time (ms): 16.33 %, highlighting the influence of longer consumer attention on the perceived attractiveness of a product.

Additional important features included Revisit count (8.1 %), Amplitude (deg) (8.1 %), and Fixation count (7.1 %), demonstrating that metrics of consumer engagement, such as the frequency of revisits and number of fixations, also contribute to the perception of attractiveness.

Predictive Ability

The model's ability to explain 57 % of the variance in attractiveness indicates a moderate correlation between visual metrics and consumer preferences (Fig. 3).

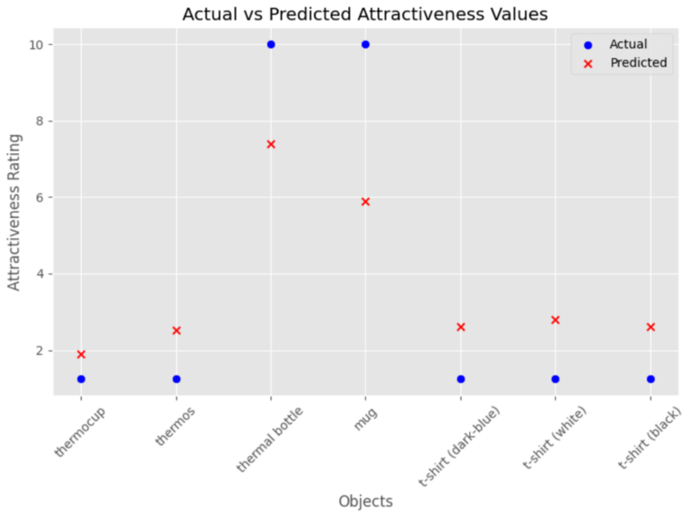

Figure 3: Actual vs Predicted Attractiveness Ratings for Promotional Objects

Note: The predictions for attractiveness ratings were obtained using Python and visualized with the help of a Random Forest Regressor model.

Discussions

The findings from this study highlight the importance of design attributes, especially visual appeal, which proved to drive consumer engagement the most. Eye-tracking metrics such as dwell time and size (cm^2), had a reliable correlation value with consumers' perceived attraction. Based on these findings, it can be suggested that larger promotional products are much more likely to be viewed as attractive. Therefore, universities should give priority to products with more surface area, like clothing or tote bags, in order to improve visual appeal. Products that promote longer visual attention — whether through functional features, symbolic imagery, or layered design elements — are also better at drawing in customers. Designing visually appealing items that encourage repeated focus, for example, by employing strategic color contrasts or balanced logo placement, is further highlighted by metrics like revisit and fixation counts. These results lend credence to a data-driven strategy for product design optimization that matches visual attributes with trends in customer engagement and attention.

These results also can suggest that consumer behavior is influenced by a blend of bottom-up factors, driven by the inherent characteristics of a product, and top-down factors, shaped by consumers' prior knowledge or expectations. As Pieters and Wedel (2004) argue, bottom-up attention is automatic and heavily guided by visual cues such as size, layout, and color, which naturally capture consumer attention. Our study's findings, where clothing items received higher engagement, align with these insights, as clothing often stands out visually and is strongly associated with consumer identity or needs. In contrast, items like stationery, which lack this emotional resonance, generated less engagement.

The significant preference for clothing (81 %) indicated by the survey responses reinforces the idea that products with higher aesthetic appeal tend to capture more attention and are more likely to be remembered by consumers (Alsharif et al., 2023) and consistent with the findings of eye-tracking results. This aligns with previous researches (Kahneman, 2011; Ariely & Berns, 2010), which discuss how neuromarketing can uncover hidden preferences in consumers behavior and preferences.

Additionally, the pattern of higher engagement with clothing items can be understood through the lens of Hedonic Versus Utilitarian Purchases (Li et. al, 2020). Hedonic purchases, such as clothing, are driven by emotional gratification and personal identity, leading to stronger consumer engagement. Clothing items often evoke a sense of self-expression and are linked to social status, making them more emotionally resonant compared to utilitarian products like stationery. The emotional appeal of clothing naturally generates greater attention and sustained engagement, reinforcing the idea that hedonic products are more likely to engage consumers.

The results of this study are consistent with earlier research that emphasizes the significance of visual cues in influencing consumers' choices. Alsharif et al. (2023) found that visually appealing products attract more attention and increase engagement. Our study supported the important role that visual attention plays in influencing consumer preferences, which is in line with the findings of Kim et al. (2024) and Xie et al. (2024). According to the findings, clothing and other items with higher visual salience are more likely to draw in customers.

However, this research takes a more thorough approach by using machine learning models like Random Forest Regressor to predict consumer behavior, in contrast to traditional studies that frequently rely on descriptive metrics. By providing deeper insights, applying machine learning models to eye-tracking data greatly enhances the capacity to predict consumer preferences, as Unger et al. (2023) point out. Our study offers a new framework for comprehending hidden patterns in consumer behavior, especially in the way that design elements affect how attractive products are perceived, by combining these predictive models.

The study's conclusions offer helpful suggestions for enhancing Almaty Management University's approach to product promotion:

- Focus on Clothing

Almaty Management University ought to think about growing its clothing line in light of the high demand for apparel. Highlighting bold, eye-catching designs could enhance the visual appeal of these products, increasing consumer engagement.

- Improve Visual Appeal

Since design attractiveness was highly rated by respondents (4.33/5), Almaty Management University should invest in high-quality graphics and designs, ensuring they are unique and more visually appealing to the target audience.

It is critical to acknowledge this study's limitations. First of all, the reliability of these results might be enhanced by a larger sample size. Additionally, customer perceptions and decisions may also have been impacted by variables like socioeconomic status and individual preferences. Belch & Belch (2009) emphasize how crucial a customer's personal objectives and feelings are to their ability to focus and make decisions.

Future studies could investigate a number of approaches to improve the results and address present limitations in light of this study:

- Increase sample size

Including a larger range of demographics in the sample may yield more in-depth information about how different customer preferences impact engagement. This would support cross-market validation of the results.

- Incorporate personal preferences and psychographic profiling

Future studies should take individual differences in motivation, lifestyle, and identity expression into consideration, given the symbolic and emotional value frequently associated with promotional items. Techniques like personality-based segmentation or brief surveys may be able to reveal trends in the use and appeal of products.

In summary, the discussion section highlights the importance of certain characteristics of promotional products. In particular, visual appeal emerged as the second most important product attribute after price, according to the survey results. Combining this data with metrics obtained from eye-tracker, the study shows that consumers are subconsciously drawn to visually appealing products, in particular to clothing. In our study, we used these metrics in machine learning models to predict consumer behavior — namely, how attractive promotional products are perceived to be. The results highlight the effectiveness of implementing neuromarketing tools in studying consumer behavior. It can reveal hidden patterns in physiological responses that traditional methods may miss. And based on these findings, universities should further prioritize larger products with more surface area, as they are more likely to be perceived as attractive, and include visually appealing elements that stimulate prolonged and repeated attention.

Conclusions

This study, conducted at the Almaty Management University, shows how certain design elements affect consumer interactions with promotional products. The survey revealed that clothing items were consistently rated as the most attractive products. The eye-tracker results also undermined this pattern, as these items also scored high in the AOI-metrics. The combination of survey data and neuromarketing tools provides important insights into how design attributes, such as size and layout, influences consumer decision-making and the perceived attractiveness of promotional products. Further analysis through machine learning models, such as Random Forest, brought important insight into the key parameters that could influence the perception of the attractiveness of items.

The results show that, particularly with respect to the apparel market, consumers tend to be attracted more to highly dressed aspects rather than things that are less designed. This aligns with the findings of Janiszewski (1998), which suggest that larger and more visually prominent stimuli tend to garner more interest. The study also confirms that eye-tracking metrics like dwell time and size (cm2) are reliable indicators of consumer interest. Our study revealed a clear correlation between these metrics and attractiveness ratings. For marketers, this means that improving the visual design of promotional products can significantly increase consumer engagement.

Although the study offers valuable information, it should be noted that it has several limitations. The results' representativeness may be limited by the 16-person sample size. The findings would be more applicable with a larger sample. Furthermore, to conduct a longitudinal research would offer an understanding of how engagement and appeal are changed in relation to the dynamic trends of the ever-changing market, culture, and economic conditions.

This research highlights that integrating advanced technology such as eye tracking, machine learning, etc., is important in marketing strategies. It gives marketers a deeper understanding of consumer behavior, from which improved and efficient promotional materials can be developed. The results showed that the visual appeal usually had a considerable effect on customer engagement. In conclusion, institutions like Almaty Management University can enhance their promotional strategies by focusing on the visual elements that most effectively capture consumer attention.

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