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Machine Learning Based Approach for Exploring Online Shopping Behavior and Preferences with Eye Tracking

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Abstract. In light of advancements in information technology and the widespread impact of the COVID-19 pandemic, consumer behavior has undergone a significant transformation, shifting from traditional in-store shopping to the realm of online retailing. This shift has notably accelerated the growth of the online retail sector. An essential advantage offered by e-commerce lies in its ability to accumulate and analyze user data, encompassing browsing and purchase histories, through its recommendation systems. Nevertheless, prevailing methodologies predominantly rely on historical user data, which often lack the dynamism required to comprehend immediate user responses and emotional states during online interactions. Recognizing the substantial influence of visual stimuli on human perception, this study leverages eye-tracking technology to investigate online consumer behavior. The research captures the visual engagement of 60 healthy participants while they engage in online shopping, while also taking note of their preferred items for purchase. Subsequently, we apply statistical analysis and machine learning models to unravel the impact of visual complexity, consumer considerations, and preferred items, thereby providing valuable insights for the design of e-commerce platforms. Our findings indicate that the integration of eye-tracking data into e-commerce recommendation systems is conducive to enhancing their performance. Furthermore, machine learning algorithms exhibited remarkable classification capabilities when combined with eye-tracking data. Notably, during the purchase of hedonic products, participants primarily fixated on product images, whereas for utilitarian products, equal attention was dedicated to images, prices, reviews, and sales volume. These insights hold significant potential to augment the effectiveness of e-commerce marketing endeavors.

Keywords: recommender systems, eye tracking, shopping preferences, machine learning, consideration factors.

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1. Introduction

In recent years, the COVID-19 pandemic and the widespread adoption of computer equipment and the internet have led to a significant shift in consumer behavior, with a growing preference for e-commerce over physical retail shopping. The Ministry of Economy of Taiwan reports a steady annual increase in online sales, reaching NT$430.3 billion in 2021, a 24.5% year-on-year growth that constituting 10.8% of the total retail industry, a record high. The e-commerce sector shows continuous growth potential. Understanding consumers is critical for the success of e-commerce, which relies on three key elements: quality products, well-designed websites, and effective marketing. Successful platforms like Amazon and Netflix owe part of their triumph to their recommendation systems, which employ vast amounts of data (e.g., product data, user interactions, behavior, and personal information) and robust algorithms to predict products of interest to customers. Personalized recommendations contribute to increased sales, user satisfaction, and platform traffic, as evidenced by approximately 35% of Amazon purchases and 75% of Netflix content views originating from personalized recommendations [1]. Visual stimuli significantly impact consumer purchase intentions, accounting for 87% of sensory information received by humans [2–4]. Eye-tracking technology, utilizing advanced sensors and instruments, enables the detection of human visual activity, providing insights into consumer interests. Most e-commerce platforms rely on historical shopping and browsing data to create recommendation systems [5]. However, for new platforms or customers without such data, the absence of effective recommendations remains a challenge. Eye-tracking addresses this limitation by analyzing real-time consumer visual activity, offering precise insights into consumer psychology and behavior, thus enhancing recommendations for new customers and platforms. Recent developments in eye-tracking systems using webcams have reduced costs, making eye-tracking more prevalent [6, 7]. However, the vast amount of consumer data collected by e-commerce platforms burdens the system, prompting a shift towards machine learning and deep learning methods for more efficient data processing and analysis. This study aims to employ statistical analysis and machine learning with eye-tracking data to analyze consumers' shopping preferences and factors influencing their behavior, providing valuable insights for e-commerce platform development [8–16]. The study will collect visual activity data during online shopping using eye-tracking technology, aiming to establish a model for analyzing consumer shopping interests and validate conclusions from the literature review. Participants will wear eye-tracking devices while browsing shopping websites, and their desired purchase items will be documented. The recorded eye movement indicators and purchase choices will help achieve the study's objectives. The purpose of this study is as follows:

1. Utilize eye-tracking data combined with personal input information from participants to employ machine learning techniques in predicting participants' desired products. This would provide a reference for integrating eye-tracking data into future recommendation systems.
2. Investigate whether the complexity of product images affects eye movement indicators when participants view products. It is hypothesized that when participants view products with higher image complexity, their fixation count, fixation duration, visit duration, and visit frequency will be higher compared to products with lower image complexity.

3. Use eye movement indicators to explore participants' attention allocation to different product information during online shopping. Generally, attention level is positively correlated with fixation duration and fixation count. Therefore, this study anticipates analyzing participants' level of interest in various product information based on fixation duration and fixation count.

This research utilizes eye-tracking technology to investigate consumers' online shopping behavior and preferences, aiming to provide insights and recommendations for e-commerce platforms.
Participants in this study will wear eye-tracking devices to record eye movement data during the shopping process. After product selection, they will complete a survey to indicate their intended purchases. The data analysis section will involve examining and discussing the collected eye movement data.The research comprises six chapters. Chapter One serves as an introduction, providing background information and motivation for using eye-tracking analysis in online shopping and outlining the research objectives. Chapter Two presents a literature review, discussing past relevant studies, including eye-tracking technology and its commercial applications, machine learning classification algorithms, related eye movement classification research, and effectiveness, as well as basic recommendation system algorithms and eye-tracking applications. Chapter Three outlines the research methodology, detailing the participants, equipment, experimental procedures, data analysis, and the analysis model framework. Chapter Four showcases the experimental results, presenting the predictive effectiveness of eye movement data in determining shopping preferences, analyzing the impact of product image complexity on eye movement indicators, and exploring consumers' attention allocation during online shopping. Chapter Five discusses the results from Chapter Four, speculating on potential reasons for findings and addressing study limitations. Finally, Chapter Six presents the conclusion, summarizing the experimental findings and suggesting future research directions.

2. Related Work

2.1. Eye-Tracking Technology and Relevant Research in Business Behavior

Eye-Tracking Technology and Indicators Eye Tracker is a device that utilizes high-resolution cameras to capture human eye images at different intervals. Computer analysis software processes the eye data, allowing researchers to record human visual activity. Eye-tracking enables the observation of eye fixations, saccades (rapid eye movements between fixations), and changes in pupil size, among other information. Its applications are widespread, being used in neuroscience , human factors engineering , sports science , user experience research , and other fields to conduct further studies and investigations.This section introduces the important indicators of eye-tracking [17–23], eye-tracking technology has already been applied in a lot of different fields, Stember et al. found that eye tracking technology can generate segmentation masks for deep learning semantic segmentation in healthcare, achieving similar results to manually annotated masks, with the potential to enhance efficiency in radiology clinical workflow [24]. Nugrahaningsih et al. explored the use of gaze data to distinguish between Visual and Verbal learning styles, demonstrating a significant correlation when presenting information graphically and in text, offering valuable insights into the application of eye tracking technology in learning styles research [25]. Eye tracking, integrated into specialized eye-tracking devices and incorporated into PC/Pad, AR/VR/XR, automobiles, and other specific equipment, has found extensive applications in fields such as scientific research, healthcare, gaming, market research, education and training, design, and manufacturing.

Area of Interest (AOI) refers to the region of interest where researchers intend to observe participants' visual movements. Saccades are the rapid movements of both eyes between fixations, while fixations involve focusing on a specific location for a certain period. Fixations are vital indicators in eye-tracking research and are closely related to attention.

Eyes possess powerful communicative abilities, and eye contact and gaze direction are central to human communication. In various fields, the above-mentioned eye-tracking indicators can be used to study and explore human behavior. Recent years have seen extensive use of eye-tracking in the field of Human-Computer Interaction (HCI) and it holds significant development potential [26]. Therefore, this research aims to utilize eye-tracking technology to investigate consumers' online shopping behavior and gain insights into human psychology through visual communication.

Eye-Tracking and Consumer Behavior Eye movement indicators, documenting consumers' visual engagement during shopping, can reveal valuable insights into their purchasing decisions. Past research has highlighted a direct correlation between high eye movement metrics (like Number of Fixations, Total Fixation Duration, Total Visit Duration) and consumer engagement, especially with particular products [27]. Furthermore, studies using these metrics have successfully predicted product attractiveness and potential purchases [28, 29].

It's noteworthy, however, that the utilization of predictive models with these metrics remains under-explored. Likewise, studies have identified gender-based differences in consumers' attention to product information and their opinion through eye movement indicators [30]. Consequently, this study aims to leverage eye movement data like fixation count and duration, and visit duration to predict consumer product interest, providing businesses with critical insights for strategic development.

Image Complexity and Eye Movement Data The eyes, acting as information conduits to the brain, are influenced by visual stimuli, affecting interpretation time and eye movement data. Visual stimuli intensity, related to stimulus complexity, can be divided into feature complexity (e.g., color, brightness), element complexity (diversity of elements, irregularity), and arrangement complexity (irregular or asymmetric arrangement). Studies show that on e-commerce platforms, product image background complexity impacts consumer attention; products with high complexity garner higher attention, while medium complexity enhances purchase intent [31]. Likewise, images with more elements increase fixation count and visit duration due to their information-rich complexity [32].

Therefore, this study investigates whether image complexity affects eye movement data, validating prior research consistency. The results will help determine image complexity as a potential factor when integrating eye movement data into recommendation systems.

2.2. Machine Learning

Supervised Learning Supervised Learning, a key machine learning branch known for its accuracy, utilizes training and test datasets [33–35]. The training dataset, comprising features and corresponding labels, aids in developing a model that can map these inputs to outputs and predict new data. This iterative learning model constantly adjusts its structure for enhanced performance. The test dataset measures the model's proficiency in predicting unknown data and checks for overfitting. Supervised learning includes regression and classification models, with the former predicting numerical values and the latter categorizing data. Given this research aims to classify consumer-interest products, a classification model is employed. Subsequent sections will explore machine learning classification models, including Decision Trees, Support Vector Machine (SVM), Random Forest, and Gradient Boosting Trees.

Decision Tree, DT The structure of a decision tree resembles an upside-down tree, composed of nodes and branches. Starting from the root node, which represents the entire sample set, each internal node represents a rule. Based on the rule's conditions, the data is branched out, and decisions are made. This process is repeated until all data is classified, and the nodes with completed branches become the leaf nodes [36]. For classification problems, decision trees often use metrics such as Information Gain, Gain Ratio, and Gini Index to evaluate the quality of branches. These metrics are explained as follows:

1. Information Gain
   First, we need to define the measure of uncertainty for a random variable, which is called entropy. Let's assume a dataset D, and the entropy of D is given by Equation 1:
   $$Entropy(D) = -\sum_{k=1}^{K} p_k \log_2 p_k \tag{1}$$
   Here, p_k represents the proportion of class k in the dataset D, and log_2 is the logarithm with base 2, which ensures that the entropy falls within the range of 0 to 1. Information Gain represents the change in entropy before and after a split. It is calculated based on a rule A that partitions the sample data D into j nodes. The number of samples in the $i-th$ node is denoted by number of D_i. The formula for Information Gain, as given by Equation 2, is used to measure the effectiveness of rule A in partitioning the samples:
   $$Gain(D, A) = Entropy(D) - \sum_{i=1}^{j} \frac{numberofD_i}{numberofD} Entropy(D) \tag{2}$$
   A larger Information Gain indicates that the rule A results in greater purity of sample partitioning. Consequently, the rule with the highest Information Gain is selected to perform the split in the decision tree.
2. Information Gain Ratio
   Information Gain prefers choosing rules that can branch into more subsets of data to maximize data purity. However, using Information Gain as an evaluation criterion for branching can lead to decision trees with reduced generalization ability, resulting in

adverse effects on classification problems. Therefore, the Information Gain Ratio is introduced as an improvement to address this issue, showing a preference for rules that branch into fewer subsets of data, as shown in Equation 3.

$$GainRatio(D, A) = \frac{Gain(D, A)}{-\sum_{i=1}^{j} \frac{numberofD_i}{numberofD} \log_2 \frac{numberofD_i}{numberofD}} \tag{3}$$

3. Gini Coefficient
   The Gini coefficient is another method for calculating impurity.

$$Gini(\mathrm{D}) = 1 - \sum_{k=1}^{K} p_k^2 \tag{4}$$

Support Vector Machine SVM's key principle involves using kernel functions to project low-dimensional inseparable data into high-dimensional space, where it locates an optimal hyperplane that efficiently distinguishes different classes of data [37, 38]. Additionally, SVM strives to optimize the margin of separation, ensuring the largest possible boundary region. Its mathematical solution is as follows:

$$\max_{\mathrm{w}} \left\{ \frac{2}{\|w\|} \right\} subjecttoy_i \left(w^T x_i + \gamma I \right) \geq I, \forall i = 1, \ldots, n \tag{5}$$

The support vector machine (SVM) model can be viewed as an optimization problem, where the equation $w^T x_i + \gamma I$ represents the separating hyperplane. The objective is to maximize the margin of separation while ensuring the ability to classify different types of data, as shown in Equation 5.

Random Forest Random Forest's classification result of each tree is resolved via majority voting, determining the final outcome [39]. As part of the bagging algorithm [40], Random Forest applies the law of large numbers and random ensembles, significantly mitigating the risk of decision tree overfitting.

Extreme Gradient Boosting XGBoost generates trees in a sequential manner. The decision trees generated later are focused on reinforcing the learning and correcting errors from the previous trees, creating interdependence among the trees. Additionally, XGBoost incorporates regularization terms $L1/L2Regularization$ into its objective function to control the model's complexity and reduce the risk of overfitting [41]. Below is a brief explanation of the objective function used in XGBoost:

$$Obj(t) = \sum_{i=1}^{n} l \left(y_i, \widehat{y}_i^{t-1} + f_t\left(x_i\right) \right) + \Omega\left(f_t\right) + constant \tag{6}$$

The objective function of Extreme Gradient Boosting (XGBoost) model consists of two components, namely the loss function l and the regularization function Ω. The loss function is used to measure the error between actual values and predicted values, while the regularization function serves as a penalty term to control the model's complexity and prevent overfitting.

Eye Tracking Data and Machine Learning Eye tracking data analysis has increasingly incorporated machine learning algorithms in recent years. Schweikert et al. employed AdaBoost, Mixed Group Ranks (MGR), RF, and Multi-layer Combinatorial Fusion (MCF) to predict image attractiveness using visual data such as the final 200 milliseconds of fixation time, total visit duration, and movement count between facial features. The precision of AdaBoost and RF was 0.938 and 0.949, respectively, signifying both ensemble algorithms' accuracy in predicting such data. The MCF algorithm also outperformed MGR, indicating its potential for further refinement [42]. Additionally, machine learning has been used with eye tracking data in business, with Pfeiffer et al. utilizing algorithms like LR, RF, and SVM to differentiate between goal-directed and exploratory search behaviors in physical and VR shopping scenarios. Notably, SVM excelled in classification accuracy, with all three algorithms achieving over 70% accuracy and demonstrating efficacy in small sample sizes [16]. The studies underscore machine learning's competence in classifying eye tracking data and its enhanced interpretability relative to deep learning. These algorithms not only rank indicator importance, aiding in identifying critical predictive factors, but also offer profound managerial insights. Hence, this study seeks to use machine learning to classify eye tracking data in consumer research.

2.3. Recommendation System

Collaborative Filtering Recommendation Collaborative Filtering (CF) is a recommendation method based on a user's past purchase behavior and ratings given to products within the system, as well as the collaborative behavior and ratings of other users. Through algorithms, it calculates the similarity of users' preferences and provides product recommendations accordingly [43–45]. As shown in Figure 1, if User A has purchased and rated products 1, 2, and 4 positively, and User C has purchased products 1 and 4 and given similar ratings as User A, then collaborative filtering algorithms identify the similarity in preferences between User A and User C. As a result, the system automatically recommends product 2 to User C. Collaborative filtering recommendation has the advantage of being able to recommend suitable products based on consumers' preferences. However, it also faces two major problems: firstly, if the majority of users have not rated the products, there will be a lack of essential recommendation basis, resulting in the sparsity problem; secondly, when new users enter the system without past purchase and rating history, or when new products have no ratings, collaborative filtering recommendation lacks historical information and becomes ineffective, which is known as the cold start problem [5].

Content-Based Filtering Recommendation Content-Based Filtering (CBF) is a recommendation method that relies on the features of products themselves, the products that users search for, the features of previously purchased products, and the information provided by users when they join the platform. Through algorithms, it calculates the preferred product features of users and generates recommendations for products that users might be interested in, as depicted in Figure 2. Content-Based Filtering does not require the use of other users' data and solely relies on the comparison and recommendation of individual users' preferences and product features. Therefore, during the early stages of platform construction with limited user data and product ratings, Content-Based Filtering can effectively address the sparsity problem and cold start problem encountered in collaborative filtering recommendations. However, Content-Based Filtering has two main drawbacks: Firstly, since it calculates recommendations based on product features, it necessitates the appropriate and comprehensive definition of features for each product [46]. Secondly, Content-Based Filtering's primary limitation lies in using consumer preferences for product features as the basis for recommendations, which tends to recommend products of the same type. Consequently, new products with unique features might not be effectively recommended, leading to a lack of exposure to diverse products, known as the Over Specialization Problem [47].

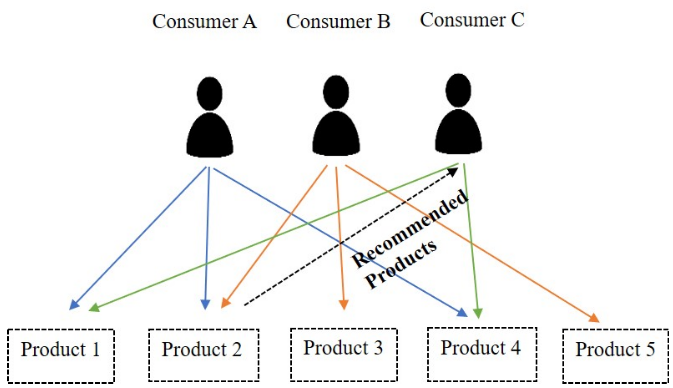

Fig. 1. Collaborative filtering recommendation

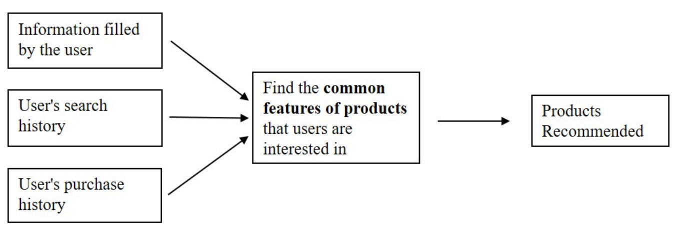

Fig. 2. Content-based filtering recommendation

Hybrid Recommendation and Eye Tracking Applications In response to the inherent constraints of single recommendation methods, research has focused on Hybrid Recommendation [48], combining different algorithms to improve basic systems. For instance, Basiri et al. utilized the Ordered Weighted Averaging (OWA) algorithm [49] to calculate weights for five classifiers, effectively addressing the cold start problem for new users or products [50]. Walek and Fojtik, in 2020, introduced a hybrid method incorporating an expert system for final ranking, which outperformed traditional methods in movie recommendations [51]. While existing website-based recommendation systems lack dynamic

channels for capturing real-time user experiences, the maturation of eye-tracking technology has offered deeper insights into user behavior. Hence, recent studies have begun integrating eye-tracking indicators into systems for more precise recommendations. For example, Song and Moon combined gaze indicators and social behavior data into their recommendation model [52], and other researchers have used webcams to record users' eye movements and facial expressions while viewing products to offer tailored recommendations [53].
These studies highlight the evolution of recommendation systems, incorporating multiple methods, including eye-tracking, to improve accuracy and user satisfaction. This integration offers a unique approach to predicting consumer interests, ensuring a more personalized user experience.

3. Research Method

3.1. Research Subjects

60 participants, devoid of eye disease history and color blindness, aged 18-35 with a minimum corrected visual acuity of 0.8, were recruited for this study, regardless of gender. Participants were sourced via social media networks. Prospective participants filled out an online form detailing the experiment's location, content, procedures, and potential risks. This ensured participant understanding prior to commitment to participation. Additionally, the form surveyed participant's eye health, contact information, and experiment scheduling availability. Suitable participants were chosen based on the form responses, and subsequently contacted for further arrangements. The study was ethically approved by the Research Ethics Committee of National Tsing Hua University.

3.2. Experimental Equipment

The Ergoneers Dikablis Glasses 3 eye-tracking system, depicted in Figure 3, was employed to monitor eye positions and document eye movements in this study. The eye-tracking system comprises a front camera (field/scene camera) capturing the environment and dual eye cameras recording binocular movements. The front camera, operating at 30 fps, records the participant's field of view with a resolution of $1920*1080$ pixels. The eye cameras, functioning at 60 Hz with a $648*488$ pixel resolution, permit exact participant eye movement tracking. The eye-tracking system is connected to the computer, and the information recorded by the front and eye cameras is transmitted to the computer. The system utilizes two-dimensional barcode (Marker) technology as the calibration reference for Areas of Interest (AOI). In this study, we aim to observe participants' visual activities during online shopping, with the focus on their gaze within the computer screen. Therefore, AOIs will be set on the information displayed on the computer screen.

3.3. Experimental Procedure

The experimental setup, conducted in an indoor laboratory, is depicted in Figure 4. The primary experimenter readies the experimental environment before participant involvement. Participants are subsequently familiarized with the eye-tracking device and calibrated to ensure precise eye movement capture. Upon verification of successful visual

Fig. 3. Ergoneers Dikablis Glasses 3 Eye Tracker (Source: Ergoneers)

activity capture, the team delineates the experimental purpose, procedure, potential risks, benefits, and data management to participants. Participants are requested to sign a consent form following explanation, preceding the actual experiment.

The experiment primarily aims to amass eye-tracking data and evaluate participant product choices during a shopping task. Three product categories, shoes, clothes, and earphones, are utilized to gauge the performance of machine learning models across diverse product categories. Test groups for shoes and earphones are segmented into low and high image complexity subgroups, to further explore image complexity impact. Participants don the eye-tracking device during the experiment, recording their eye movements while making product selections, before proceeding to subsequent product tests. Upon completion of all product category experiments, the research team facilitates eye-tracking device removal, signifying the conclusion of the experiment.

3.4. Experimental Design

Experimental Material Selection Three daily-use products, shoes, clothes, and earphones, were selected for this study, categorized based on their type. Dhar and Wertenbroch's research shows that consumer buying decisions are influenced by hedonic and utilitarian consideration [54], thus allowing for a classification into hedonic and utilitarian goods. Utilitarian goods, including items like earphones, are characterized by functional utility, with consumers prioritizing aspects such as functionality, quality, and price. In contrast, hedonic goods, such as clothes, offer experiential consumption, providing pleasure and enjoyment. The experimental products, shoes and clothes (hedonic goods) and earphones (utilitarian goods), were classified to investigate the variation in consumers' attention to product information due to differing product attributes. To account for previous research showing the influence of image complexity on eye-tracking data and to ensure the accuracy of machine learning eye-tracking models, three product images of similar complexity were selected for each product category. The study aims to assess the impact of image complexity on eye-tracking metrics. The test groups for shoes and earphones

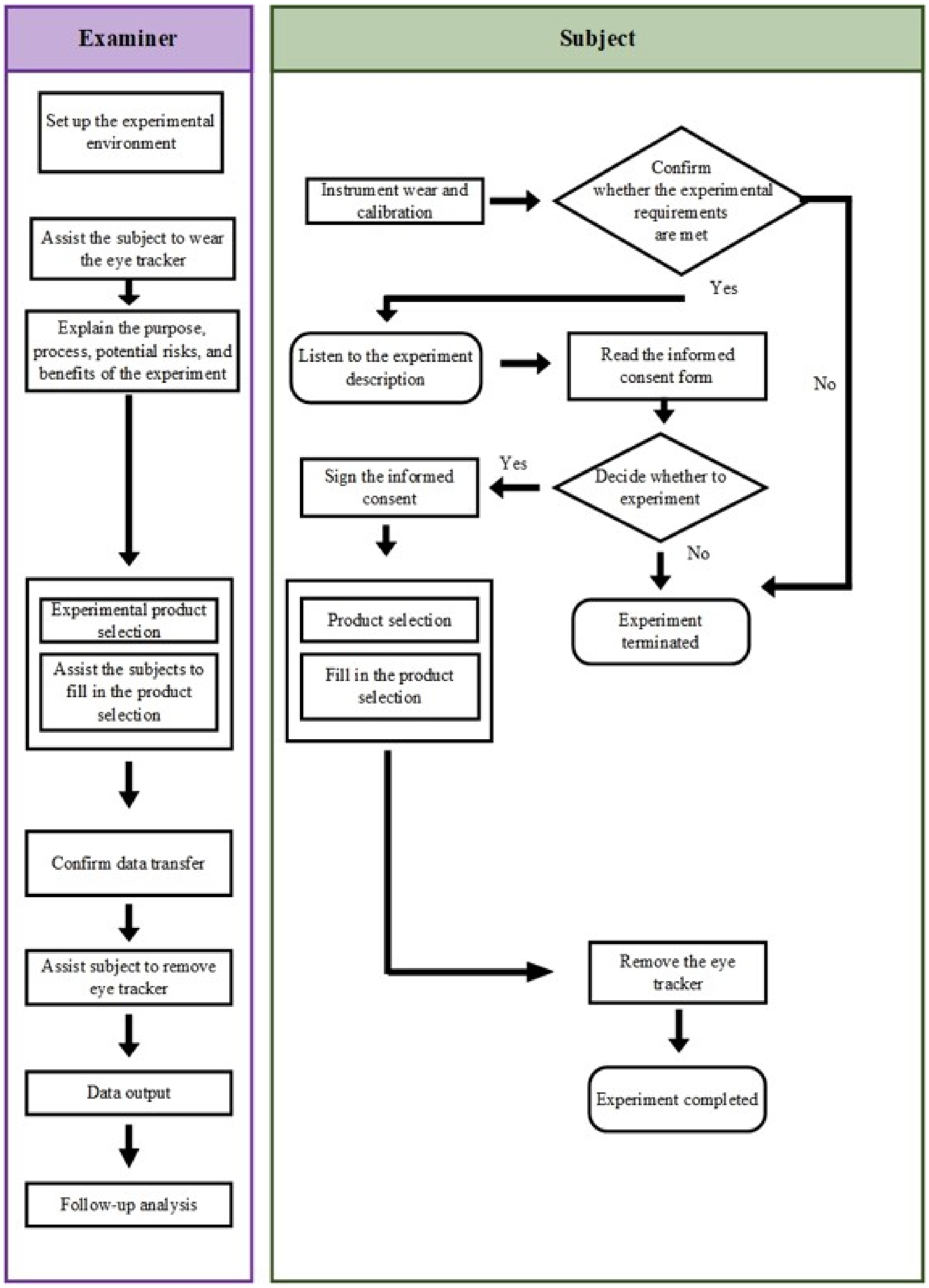

Fig. 4. Experiment Flowchart

were subdivided into low and high image complexity subgroups for comparative analysis of eye-tracking data. Following Qiuzhen et al.'s research, this study defines image complexity through feature complexity, element complexity, and arrangement complexity. Images with low complexity feature only the product in Figure 5, while those with high complexity contain more than four elements and colors, arranged irregularly and diversely in Figure 6.

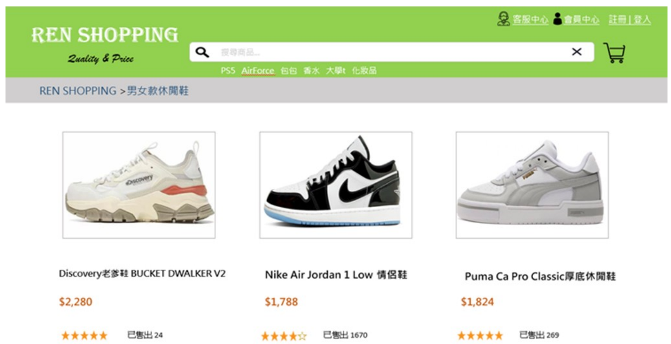

Fig. 5. Products with low image complexity

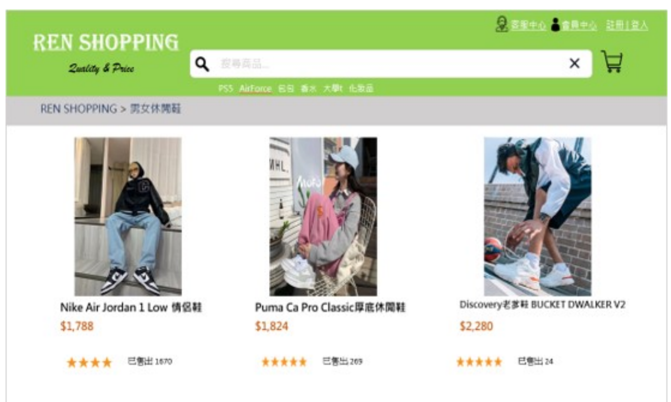

Fig. 6. Products with high image complexity

Eye-tracking Data The main Areas of Interest (AOIs) in this experiment will be set to the product information displayed on the screen, which can be divided into four major areas: all product information, product images, product prices, and product ratings and sales volume, as shown in Figure 7. The shaded regions represent the AOI areas. Subsequent analysis will utilize participants' gaze and visit data within these AOIs to observe their visual activities and attention allocation during the shopping task. Specifically, for the eye-tracking recommendation data, the large AOI covering all product information (gray region in Figure 7) will be selected as the basis for analysis. For the experiment on image complexity and eye-tracking data, the data within the AOI of product images (blue region in Figure 7) will be used for analysis. For the experiment analyzing attention allocation with eye-tracking data, data from three AOIs will be used: product images (blue region in Figure 7), product prices (orange region in Figure 7), and product ratings and sales volume (green region in Figure 7). The data used for analysis in this experiment were

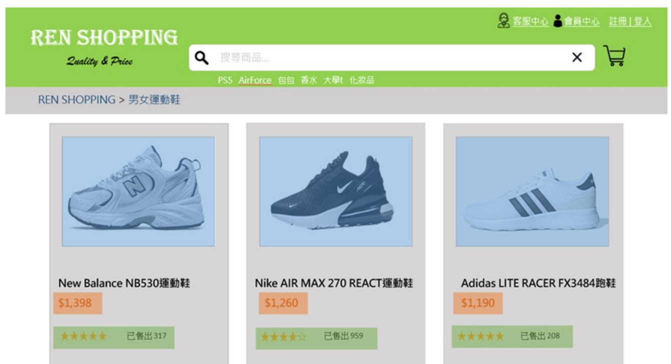

Fig. 7. Product information AOI

obtained from the D-LAB analysis software. The data description is as follows:

1. Session Duration: The time taken to complete a task, which in this study can be considered as the time taken for product selection.
2. Number of Glances: The frequency of visits to the Areas of Interest (AOIs).
3. Total Glance Time: The overall time spent visiting the AOIs.
4. Glance Location Probability: This metric compares the attention distribution among different AOIs as the formula 7 shows:

$$GlanceLocationProbability = \frac{NumberofGlancestoanAOI}{\sum NumberofGlancestoAOI1, AOI2} \tag{7}$$

5. Number of Fixations: The frequency of fixations or instances where the gaze is fixated on a particular point.
6. Total Fixation Time: The cumulative duration of all fixations, representing the total time spent with gaze fixed on various points of interest.

Experimental Environment Design The present experiment simulates the environment of consumers shopping online and to ensure that the eye tracker can accurately capture the entire website interface, participants' eye distance from the screen is controlled to be approximately 50 centimeters. Additionally, the height of the chair will be adjusted according to the participants' different heights, as shown in Figure 8.

Fig. 8. Experimental Environment

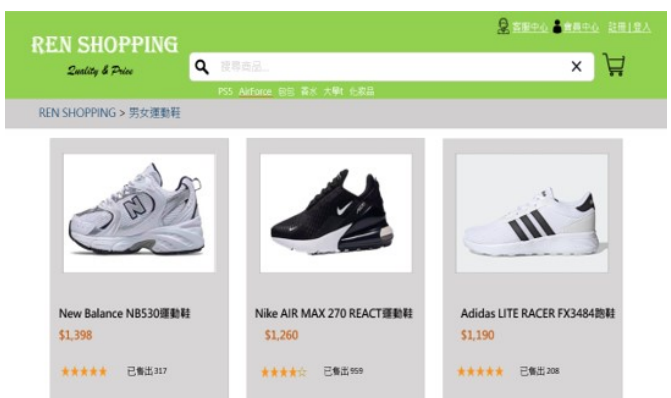

Fig. 9. AOI of the forecasting model

3.5. Machine Learning Eye Movement Prediction Model

This study aims to predict participant product choices using eye movement data within various product Areas of Interest (AOIs). Three products, each associated with its AOI, are selected for the test group. Eye movement data within these AOIs will inform the machine learning model, facilitating the development of a recommendation model grounded in eye movement behavior in Figure 9.

Given the diverse input data and categorical product choice data, a machine learning model is employed for classification prediction. A supervised learning approach, utilizing a Multiclass Classification model, is employed to predict product interest. Feature data comprises preprocessed eye movement data, including total glance time, total glance frequency, AOI attention ratio, and other relevant metrics aligned with product eye movement behavior. Participant purchase choices serve as model labels during analysis, resulting in preprocessed eye movement data as input and predicted product interest as output in Figure 10. The study classifies products of interest into three categories, influenced by participant preferences, potentially leading to imbalanced data and lower prediction performance. To address potential imbalance, the Synthetic Minority Oversampling Technique (SMOTE) will be used to augment minority class data before applying machine learning classification models. Previous literature reveals promising results in classifying eye-tracking data using Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF) [16, 42, 55, 56]. In addition, the XGBoost (XGB) classification model is commonly used in recent machine learning competitions. This study will apply and compare four different classifiers - DT, SVM, RF, and XGB. Model validation will be executed using a Confusion Matrix to assess performance. In the Confusion Matrix, True Positive (TP) and True Negative (TN) represent correctly predicted positive and negative instances, respectively, while False Positive (FP) and False Negative (FN) indicate incorrect positive and negative predictions. The study uses Accuracy, Precision, Recall Rate, and F1-Score as performance metrics. Accuracy represents the ratio of correctly classified instances, Precision indicates the ratio of correct positive predictions, Recall Rate defines the proportion of correct positive classifications among actual positives, and F1-Score is the harmonic mean of Precision and Recall Rate.

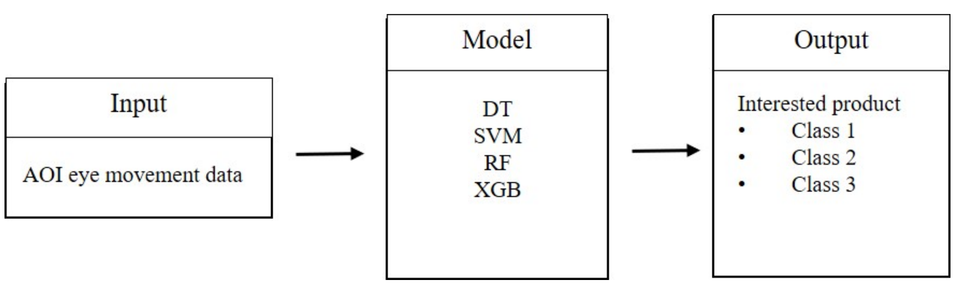

Fig. 10. Diagram of machine learning data

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

$$F1 - Score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}} \tag{11}$$

3.6. Statistical Analysis

Eye-tracking data and Image Complexity Wang's web design study suggests product images with greater background complexity draw more consumer attention, due to the multitude of features influencing consumer cognitive processing and fluency, resulting in extended time spent understanding the product. Thus, products with higher background complexity yield greater fixation duration and frequency than those with less complexity [31]. Vu et al. observed a significant increase in both fixation frequency and visit duration as the number of image elements increased, as larger and more complex information requires increased processing time [32]. Building upon these findings, this experiment seeks to explore the impact of image complexity on eye-tracking data within e-commerce platforms. Image complexity is thus categorized into low and high groups, with experiments performed using images from each complexity level. The study analyzes eye-tracking indicators including fixation duration, fixation frequency, visit duration, and visit frequency. Eye-tracking data from the two complexity groups are compared to discern differences in eye movement patterns. For the eye-tracking data and shoe image complexity, the following hypothesis H1 is proposed: Participants will focus more attention on shoe images with higher background complexity. Subsequently, the following individual hypotheses (H1a, H1b, H1c, H1d) are proposed for the shoe group eye-tracking data:

1. *H1a: As the complexity of shoe images increases, consumers' visit duration also increases.*
2. *H1b: As the complexity of shoe images increases, consumers' fixation duration also increases.*
3. *H1c: As the complexity of shoe images increases, consumers' visit frequency also increases.*
4. *H1d: As the complexity of shoe images increases, consumers' fixation frequency also increases.*

Likewise, for the eye-tracking data and earphone image complexity, the hypothesis H2 is proposed: Participants will focus more attention on earphone images with higher background complexity. Subsequently, the following individual hypotheses (H2a, H2b, H2c, H2d) are proposed for the earphone group eye-tracking data:

1. *H2a: As the complexity of earphone images increases, consumers' visit duration also increases.*
2. *H2b: As the complexity of earphone images increases, consumers' fixation duration also increases.*
3. *H2c: As the complexity of earphone images increases, consumers' visit frequency also increases.*

4. *H2d: As the complexity of earphone images increases, consumers' fixation frequency also increases.*

For the observation of image complexity and eye-tracking data, this study employs paired-samples t-tests. The eye-tracking data for each group are obtained by summing the visit duration, fixation duration, visit frequency, and fixation frequency of the three product images in each group. A significance level of 0.05 is used for the comparison of eye-tracking data between the groups, as shown in Figure 11.

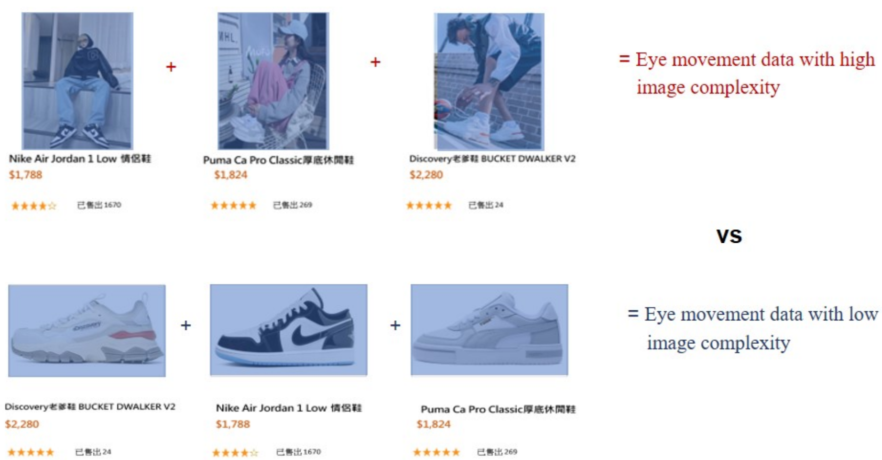

Fig. 11. Diagram of image complexity calculation

Eye Movement Data and Purchase Consideration Factors Hwang and Lee conducted eye-tracking research to investigate consumer attention allocation during online shopping. The results showed that consumers' highest attention was on product information, including product images, product prices, and product descriptions. The next highest attention was on consumer opinions [28], but there was no further exploration of individual product information such as product images and prices. Therefore, this experiment aims to use eye-tracking to further study consumer attention allocation to individual product information when shopping online. Individual product information includes product images, product prices, product ratings, and sales volume, these three major aspects. In this study, we defined separate Areas of Interest (AOIs) for these three pieces of information, as shown in Figure 12. We intend to use Total Fixation Duration (TFD) and Number of Fixations (NF) within these three AOIs as indicators of participant attention to observe their attention allocation during shopping.
Since this study categorizes shoes and clothing as hedonic products, it is hypothesized that when consumers shop for these two categories, they primarily consider the appearance of the product, followed by factors such as price and ratings. Hypotheses H3 and H4 are proposed: For shoes and clothing, participants' attention to product images will be

greater than their attention to product prices, ratings, and sales volume. Attention to product prices and ratings, as well as sales volume, will be equal. Furthermore, since attention is composed of both the time spent viewing and the number of times viewed, hypotheses are proposed for Total Fixation Duration (TFD) and Number of Fixations (NF): For shoes (H3a, H3b) and clothing (H4a, H4b):

1. *H3a: TFD for images > TFD for prices = TFD for ratings and sales volume*
2. *H3b: Number of fixations (NF) for images > NF for prices = NF for ratings and sales volume*
3. *H4a: TFD for images > TFD for prices = TFD for ratings and sales volume*
4. *H4b: Number of fixations (NF) for images > NF for prices = NF for ratings and sales volume*

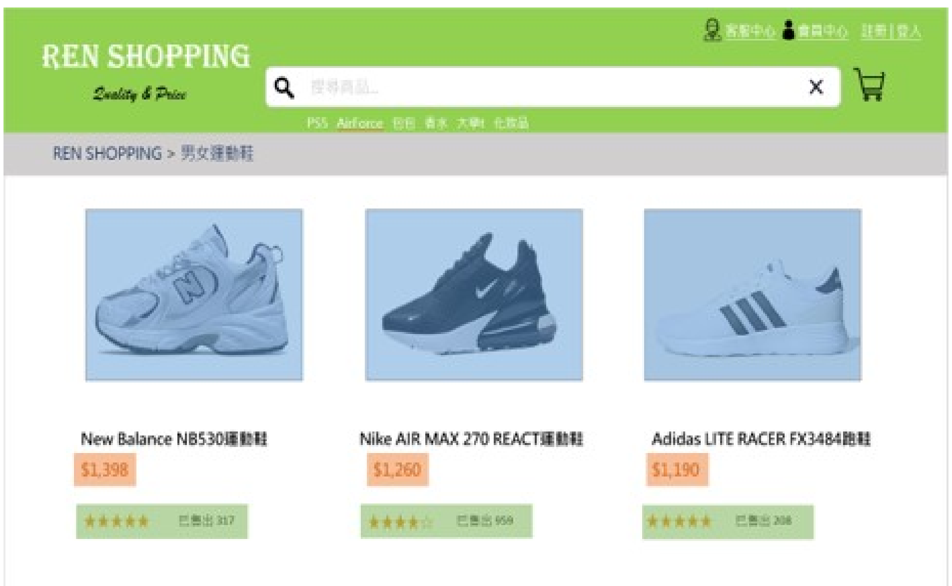

Fig. 12. Product Information AOI

In this study, earphones are categorized as utilitarian products, where consumers prioritize product quality and functionality when purchasing earphones. Factors that reflect product quality during online shopping include product price and product ratings and sales volume. Therefore, it is hypothesized that when consumers shop for earphones, they will primarily consider product price and product ratings and sales volume, with product appearance being of secondary importance. Consequently, the following attention allocation hypotheses for earphones are proposed:

1. *H5a: TFD for prices = TFD for ratings and sales volume > TFD for images*
2. *H5b: NF for prices = NF for ratings and sales volume > NF for images*

This study employs a one-way analysis of variance (One-Way ANOVA) with different product information AOIs as groups, as depicted in Figure 13. It aims to compare fixation duration and fixation count separately, with a significance level set at 0.05. If there are significant differences in attention allocation among the three product information categories, post-hoc comparisons will be conducted to analyze the hierarchy of attention allocation among them.

Fig. 13. Diagram of eye-tracking data calculation for commodity information

4. Experimental Results

The experiment recruited a total of 60 participants, comprising 30 males and 30 females, with an average age of 22.7 ± 2.68 years. All participants were college students without any eye-related disorders.

4.1. Eye-tracking Machine Learning Predictive Model Performance

This study utilizes eye-tracking data as input for a machine learning predictive system to forecast participants' purchase intentions. The experiment focuses on predicting purchases within three categories: shoes, clothing, and earphones. The models used encompass Decision Trees (DT), Support Vector Machines (SVM), Random Forest (RF), Extreme Gradient Boosting (XGB), and statistical-based models. Eye-tracking data, comprising total visit time, visit frequency, visit ratio, total fixation time, and fixation count, were employed to segregate products into three categories - highest, intermediate, and lowest eye-tracking data. These categories were utilized as machine learning features, culminating in a total of 15 features. Each product test group contained 60 data samples, split into training and testing sets at an $8:2$ ratio. Imbalanced minority class data were counterbalanced using the SMOTE technique during training. Table 1 illustrates the performance of the models within the shoe test set. The SVM model displayed superior performance with an accuracy of 0.80256, trailed by the RF model with an accuracy of 0.78974. The statistical-based voting model demonstrated the lowest accuracy, at just 0.64358.

Table 1. Prediction performance table for the test set of shoes

Dataset	Method	Accuracy	Precision	Recall	F1-Score
Shoes	DT	0.69487	0.73333	0.69333	0.68667
	SVM	0.80256	0.82333	0.80333	0.79667
	RF	0.78974	0.81333	0.80667	0.78667
	XGB	0.77692	0.81	0.77667	0.77333
	Statistical	0.64358	0.76333	0.65667	0.63667

In the clothing test set, the performance of the models was not as prominent as in the shoe test set, as shown in Table 2. The RF model achieved the highest predictive performance with an accuracy of 0.71538, followed by the XGB model with an accuracy of 0.70513. The DT model showed the lowest accuracy, with only 0.63333.

Table 2. Prediction performance table for the test set of clothes

Dataset	Method	Accuracy	Precision	Recall	F1-Score
Clothes	DT	0.63333	0.62667	0.63	0.60333
	SVM	0.66410	0.68667	0.67	0.64667
	RF	0.71538	0.72667	0.70333	0.69
	XGB	0.70513	0.72333	0.69667	0.68
	Statistical	0.68205	0.67333	0.68333	0.64333

In the earphone test set, the performance of the models falls between that of the shoe test set and the clothing test set, as shown in Table 3. Among the models, the SVM model achieved the highest predictive performance with an accuracy of 0.74359, followed by the RF model with an accuracy of 0.73333. The Statistical model showed the lowest accuracy, with only 0.61538.

4.2. Impact of Image Complexity on Eye-tracking Data

This section examines the influence of images on attention through eye-tracking data. It compares groups with high-complexity images and groups with low-complexity images in terms of eye-tracking data, including glance time, fixation time, glance numbers, and fixation numbers, to determine whether significant differences exist. The experiment included two types of products, shoes and earphones, and presented the comparative results of image complexity between the shoe group and the earphone group. The experimental results are presented in the table 4-13 below:

Table 3. Prediction performance table for the test set of earphones

Dataset	Method	Accuracy	Precision	Recall	F1-Score
Earphones	DT	0.65128	0.6	0.57	0.56
	SVM	0.74359	0.79333	0.72667	0.72667
	RF	0.73333	0.73667	0.72333	0.72
	XGB	0.70256	0.73333	0.69333	0.69333
	Statistical	0.61538	0.61333	0.56	0.53667

Table 4. t-test of shoe selection time for different complexity groups

	Group	N	Mean	Std.	T-Value	P-Value
Product selection time	High complexity	60	19.60	9.85	2.13	0.037*
	Low complexity	60	16.82	9.45		

Table 5. t-test for total glance time between high-complexity shoe group and low-complexity shoe group

	Group	N	Mean	Std.	T-Value	P-Value
Total Glance Time	High complexity	60	7.449	6.145	0.52	0.605
	Low complexity	60	7.026	5.769		

Table 6. t-test of total fixation time between high-complexity shoe group and low-complexity shoe group

	Group	N	Mean	Std.	T-Value	P-Value
Total Fixation Time	High complexity	60	7.026	5.894	-0.85	0.400
	Low complexity	60	7.719	7.070		

Table 7. t-test for the number of glances between the high-complexity shoe group and the low-complexity shoe group

	Group	N	Mean	Std.	T-Value	P-Value
Number of Glances	High complexity	60	10.467	4.928	0.28	0.780
	Low complexity	60	10.233	6.596		

Table 8. t-test for the number of fixations between the high-complexity shoe group and the low-complexity shoe group

	Group	N	Mean	Std.	T-Value	P-Value
Number of Fixations	High complexity	60	14.07	7.97	-0.63	0.530
	Low complexity	60	14.92	10.38		

Table 9. t-test of the product selection time earphones between different complexity groups

	Group	N	Mean	Std.	T-Value	P-Value
Product Selection Time	High complexity	60	19.74	9.80	1.81	0.075
	Low complexity	60	17.93	8.44		

Table 10. t-test for total glance time between high-complexity earphones group and low-complexity earphones group

	Group	N	Mean	Std.	T-Value	P-Value
Total Glance Time	High complexity	60	4.994	3.413	-0.13	0.895
	Low complexity	60	5.047	3.561		

Table 11. t-test for total fixation time of high-complexity earphones group and low-complexity earphones group

	Group	N	Mean	Std.	T-Value	P-Value
Total Fixation Time	High complexity	60	4.579	3.190	-1.46	0.150
	Low complexity	60	5.170	4.383		

Table 12. t-test for the number of glances between the high-complexity earphones group and the low-complexity earphones group

	Group	N	Mean	Std.	T-Value	P-Value
Number of Glances	High complexity	60	7.867	4.102	-1.61	0.112
	Low complexity	60	8.800	4.977		

Table 13. t-test for the number of fixations between the high-complexity earphones group and the low-complexity earphones group

	Group	N	Mean	Std.	T-Value	P-Value
Number of Fixations	High complexity	60	11.40	6.43	-1.27	0.208
	Low complexity	60	12.70	8.67		

4.3. Product Information Attention Allocation

This study examines consumers' attention allocation during the process of purchasing products using eye-tracking data. Specifically, we compare the eye movement data related to three types of product information: product images, product prices, and product ratings and sales volume. The product categories include hedonic products such as shoes and clothing, as well as utilitarian products like earphones. The following experiment will present the attention allocation results for shoes, clothing, and earphones.The experimental results are presented in the table 14-24 below:

Table 14. ANOVA table of fixation time for three product information in the shoes test group

	DF	Adj SS	Adj MS	F-Value	P-Value
Total Fixation Time	2	1013	506.58		
Error	177	2538	14.59	34.73	0.000*
Total	179	3551			

Table 15. Post-hoc comparative analysis of total fixation time of the shoe test group

info	N	Mean	Std.
Image	60	7.295	6.021
Price	60	2.312	1.783
Reviews and sales	60	2.132	2.080

Table 16. ANOVA table of the number of fixations of the three product information in the shoe test group

	DF	Adj SS	Adj MS	F-Value	P-Value
Number of Fixations	2	1840	919.77		
Error	177	6050	34.77	26.45	0.000*
Total	179	7890			

4.4. Hypothesis Consolidation Table

The hypotheses and results of this study according to the experiment results are presented in Table 25. Subsequently, in Chapter 5, a further discussion and explanation will be provided regarding the experimental outcomes for each research item.

Table 17. Post-hoc comparative analysis of number of fixations of the shoe test group

info	N	Mean	Std.
Image	60	14.720	6.509
Price	60	8.924	5.242
Reviews and sales	60	7.178	5.871

Table 18. ANOVA table of total fixation time for three product information in the clothes test group

	DF	Adj SS	Adj MS	F-Value	P-Value
Total Fixation Time	2	774.4	387.179		
Error	177	1691.5	9.557	40.51	0.000*
Total	179	2465.9			

Table 19. Post-hoc comparative analysis of total fixation time of the clothes test group

info	N	Mean	Std.
Image	60	6.404	4.791
Price	60	2.195	1.688
Reviews and sales	60	1.835	1.692

Table 20. ANOVA table of the number of fixations of the three product information in the clothes test group

	DF	Adj SS	Adj MS	F-Value	P-Value
Number of Fixations	2	2634	1317.04		
Error	177	8674	49.01	26.87	0.000*
Total	179	11308			

Table 21. Post-hoc comparative analysis of the number of fixations in the clothes test group

info	N	Mean	Std.
Image	60	15.08	9.47
Price	60	8.367	5.810
Reviews and sales	60	6.067	4.857

Table 22. ANOVA table of total fixation time for three product information in the earphone test group

	DF	Adj SS	Adj MS	F-Value	P-Value
Total Fixation Time	2	106.6	53.311		
Error	177	1370.7	7.744	6.88	0.001*
Total	179	1477.3			

Table 23. Post-hoc comparative analysis of total fixation time in the earphone test group

info	N	Mean	Std.
Image	60	4.506	3.263
Price	60	3.067	2.258
Reviews and sales	60	2.732	2.735

Table 24. ANOVA table of the number of fixations on the three product information in the earphones test group

	DF	Adj SS	Adj MS	F-Value	P-Value
Number of Fixations	2	237.9	118.95		
Error	177	9687.1	54.73	2.17	0.117
Total	179	9925.0			

Table 25. Hypothesis Consolidation Table

Hypothesis	Valid
H1a: The higher the complexity of the shoes image, the longer the consumer's glance time	No
H1b: The higher the complexity of the shoes image, the longer the consumer's fixation time	No
H1c: The higher the complexity of the shoes image, the higher the number of glances by consumers	No
H1d: The higher the complexity of the shoes image, the higher the number of fixations by consumers	No
H2a: The higher the complexity of the earphones image, the longer the consumer's glance time	No
H2b: The higher the complexity of the earphones image, the longer the consumer's fixation time	No
H2c: The higher the complexity of the earphones image, the higher the number of glances by consumers	No
H2d: The higher the complexity of the earphones image, the higher the number of fixations by consumers	No
H3a: TFD of images TFD of prices = TFD of reviews and sales	Yes
H3b: NF of images NF of prices = NF of reviews and sales	No
H4a: TFD of images TFD of prices = TFD of reviews and sales	Yes
H4b: NF of images NF of prices = NF of reviews and sales	Yes
H5a: TFD of prices = TFD of reviews and sales TFD of images	No
H5b: NF of prices = NF of reviews and sales NF of images	No

5. Discussion

This study utilizes eye tracking metrics, such as visit and gaze duration and frequency, to enhance understanding of consumer attention in e-commerce engagements. It explores the use of machine learning techniques to predict purchasing decisions based on categorized participant eye tracking data across three product categories - shoes, clothing, and earphones. Findings suggest a promising 70% prediction accuracy, demonstrating the potential of eye tracking data in estimating consumer interest. The Random Forest (RF) and Extreme Gradient Boosting (XGB) models have been particularly successful, outperforming traditional statistical models in terms of majority voting. This indicates the benefits of these models for predicting consumer preferences using eye tracking data, especially under limited training data conditions [57]. Among them, RF shows superior performance, making it an ideal model for eye tracking recommendation systems. The experiment results suggests that eye tracking data can effectively predict consumer interests, providing a valuable tool for e-commerce platforms. The RF model, capable of integrating various features for prediction, could be combined with additional data types, such as demographics or purchase history, to enhance personalization of product recommendations. Contrary to prior literature [31], we found no significant variance in eye tracking data for different product images, irrespective of their complexity. These results could be attributed to the experimental stimuli, as high complexity images were employed. However, these findings underline the need for further research into the role of image complexity in consumer gaze behavior [58–60, 31, 32]. This research categorizes products as hedonic and utilitarian and assesses differences in consumer focus across product types. It found that product images tend to command greater attention than other elements, such as price or rating, across both product types. This emphasis on images underscores their importance in e-commerce platforms and suggests that improvements in image quality could enhance consumer engagement [61, 62]. The gaze frequency data indicates variations in consumer focus depending on the product type. For instance, consumers prioritized product appearance for shoes and clothing, while price, ratings, and sales volume were equally important for high-priced products like earphones. These findings suggest tailored promotional activities could enhance consumer engagement with different product types. Despite the insights provided, this study acknowledges certain limitations, particularly the lack of diversity among the participant pool and the experimental setting, which excluded valuable contextual information, such as browsing history. Additionally, the impact of individual differences in decision-making styles on the effectiveness of eye tracking data requires further exploration.

In conclusion, this study highlights the potential of eye tracking data in e-commerce recommendation systems. However, further research is required to overcome the existing limitations and optimize the integration of eye tracking data with other forms of data for more precise and practical recommendations.

6. Conclusions

Our proposed approach integrates eye-tracking data and machine learning algorithms to predict consumer purchasing behavior on e-commerce platforms. Notably, the Random Forest (RF) model demonstrated exceptional performance, achieving a precision rate exceeding 70%, thereby outperforming other methods when utilizing eye-tracking metrics for forecasting. Additionally, this study unveils distinct consumer preferences for hedonic and utilitarian products, providing valuable insights to guide differentiated marketing strategies aimed at enhancing consumer engagement. Product images emerge as pivotal in shaping consumer understanding, underscoring the critical role of effective design on e-commerce platforms. The integration of eye-tracking data for predicting individual product preferences holds the potential to significantly enhance e-commerce personalization, albeit necessitating adaptability due to varying levels of product page complexity. Moreover, the observed variability in browsing patterns and decision-making times across different personality traits suggests the prospect of refining predictive models through the inclusion of personality traits as predictive factors. While it is acknowledged that current webcam-based eye tracking systems have certain limitations, ongoing advancements in technology are anticipated to enhance precision, thereby making their widespread adoption increasingly feasible. The judicious utilization of eye-tracking data empowers e-commerce platforms with profound customer insights, ultimately leading to heightened customer satisfaction and increased sales by enabling more accurate tailoring of the shopping experience.

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