Designing User Experience Improvement and User Behavior Pattern Recognition Algorithms in Design Operation

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Abstract – Enhancing user experience (UX) is a key component in customer retention and sales promotion in e-commerce platforms. To build an effective UX model it is necessary to predict the user behavior more accurately and develop UX model that is tailored based on those behavior patterns. Existing models lack the ability to integrate advanced Machine Learning (ML) models to address the challenges. This study is an attempt to tackle these limitations that employs advanced AI tools to predict user behavior so that to construct an more effective UX model. The study involved 80 users from China who were aged 26 to 52, with diverse backgrounds in education, occupation, and tech proficiency. The work have employed Google Analytics, Hotjar, and FullStory to collect the user interactions and by using Generalized Sequential Pattern (GSP) algorithm, Decision Trees (DT), and Logistic Regression (LR) the work attempts to accurately predict the user behavior patterns. The results show that the model achieved better accuracy of 0.8795 and an F1 Score of 0.8610 on the test dataset. It also excelled in conversion rate (12.34%) and bounce rate (28.65%) which show effectiveness in retaining users and converting visits into actions.

Keywords – User Experience, Generalized Sequential Pattern, Machine Learning, E-commerce Platforms, Conversion Rate, Bounce Rate.

I. INTRODUCTION

User experience (UX) design is considered to be an key component in modern establishments as they directly impact the factors like the level of user satisfaction, engagement, and retention [1-3]. In an ever-increasing competitive market it is important to maintain the above factors in positive side, for that it is necessary to understand and improve the UX by using advanced analytics and Machine Learning (ML) models [4, 5]. This study is focused on behavior pattern analysis to design UX in an e-commerce platform. The focus our ecommerce platform was influenced by the fact that there is growing complexity of user interactions and the diverse preferences that modern e-commerce platforms must satisfy. Employing heuristic evaluations and A/B testing models for behavior pattern analysis have key limitations as they are static in nature and don't have the ability to adapt in real-time to changing user behaviors [6, 7]. Also such models fail to capture the subtle patterns in user interactions that reflect personalized and effective UX improvements [8].

Further models such as usability testing, user journey mapping, and basic statistical analyses have all been employed for user behavior analysis [9, 10]. But such models lack the ability to scale and adaptability as they do not integrate the advanced machine learning techniques that can dynamically learn from and respond to user data. In order to overcome these drawbacks this work attempts to design a model that combine ML models to identify user behavior pattern to design better UX. The work employ Generalized Sequential Pattern (GSP) algorithm, Decision Trees (DT), and Logistic Regression (LR) as a combined model to understand of user behavior and predict future actions so that to provide proactive UX adjustments. The GSP algorithm is employed to identify frequently repeated sequences of actions within user sessions. The DT classify user behaviors based on decision rules derived from user data [11-15]. The LR integrates the outputs of GSP and Decision Trees to model the probability of user actions. For the study user interaction form an -commerce platform specializing in electronics and home appliances was sourced, data of around 80 user interactions was collected. To collect and analyse data the work employed tools like Google Analytics, Hotjar, and FullStory was employed. The proposed model have been evaluated for different metrics and had proven its efficiency.

The paper is structured as follows: the Section 2 presents the method, Section 3 present the analysis from the findings and Section 4 concludes the work.

II. METHOD

Data Collection

The data was collected from a known e-commerce website operating in china. Data corresponding to 80 users were sourced, the users were aged between 26 to 52 years and are from both the genders who were segmented into subgroups based on age, education, occupation, and tech proficiency. The detailed description of the demography is presented in **Table 1**.

Table 1. Demographic Characteristics

Characteristic	Description
Age Range	26 to 52 years
Education	15% High school graduates, 55% College graduates, 30% Postgraduates
Occupation	30% Technology, 20% Education, 30% Healthcare, 20% Service industries
Tech Proficiency	15% Low, 45% Medium, 40% High
Gender Distribution	45% Male, 55% Female
Sample Size	80 participants
Geographical Location	60% Urban areas, 40% Rural areas
Study Duration	Six months

The study recorded detailed user interactions with the e-commerce website such as page views, clicks on product categories, time spent on each product page, additions to cart, and final purchase actions. The Google Analytics was used to track metrics like page views, session duration, and bounce rates. The Hotjar is employed to provide visual heatmaps to identify users activity and engagement and the FullStory was employed to record and replay user sessions. The following **Fig 1** shows the user interaction heatmap.

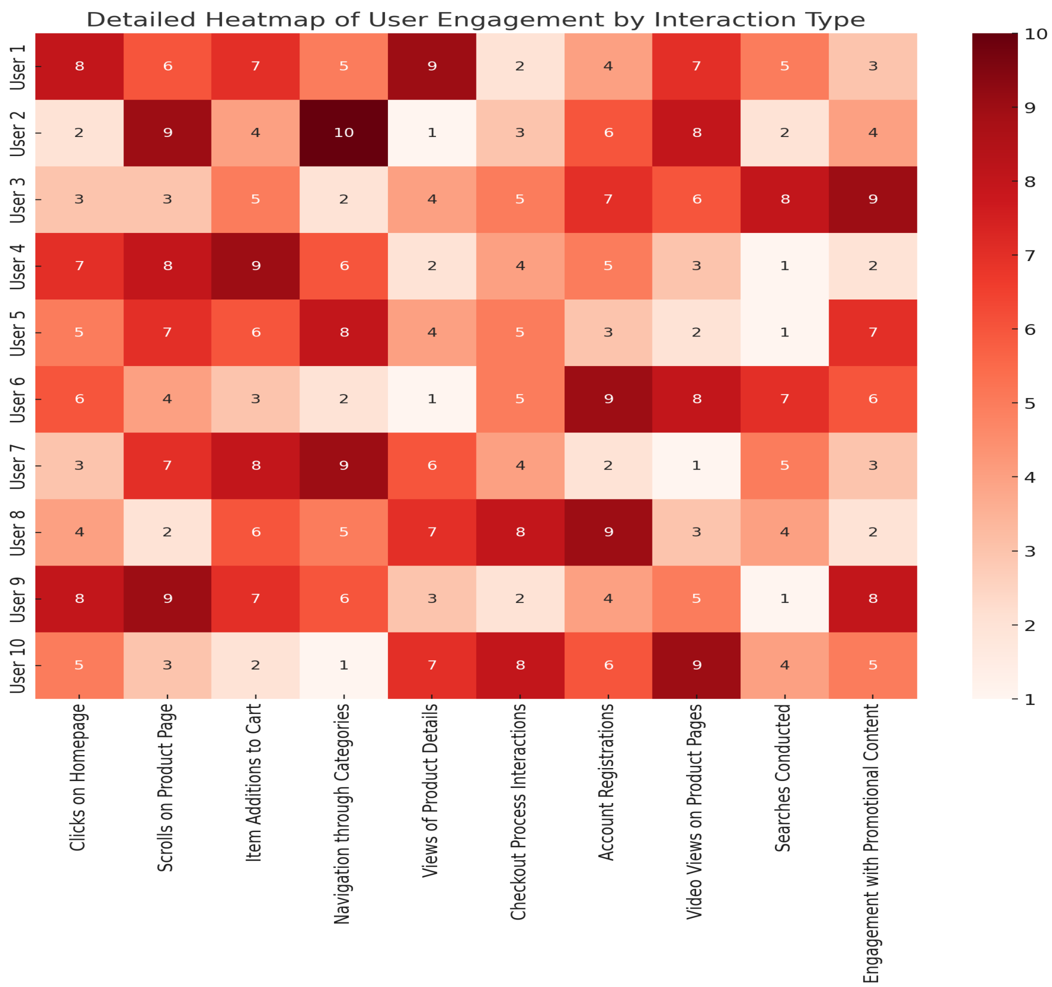

Fig 1. User Interaction Heatmap.

Machine Learning Techniques

The K-means clustering algorithm is employed to identify distinct user segments and to group users who exhibit similar behaviors. The following behavior patterns are considered for clustering: the frequency of visits (f_v), engagement levels (e_l), and purchase behavior (p_b). The K-means algorithm partitions the dataset into K clusters by minimizing the objective function J, which is defined as the sum of squared Euclidean distances between each user's behavior vector $(u_i = [f_v, e_l, p_b])$ and the nearest cluster centroid (μ_k), EQU (1).

$$J = \sum_{k=1}^{K} \sum_{u_i \in C_k} \|u_i - \mu_k\|^2 \tag{1}$$

where C_k denotes the set of users assigned to cluster k, and $\|u_i - \mu_k\|$ represents the Euclidean distance between user u_i and the cluster centroid μ_k. The algorithm involves initializing K centroids randomly, assigning each user to the nearest centroid, and then updating the centroids based on the mean of users in each cluster. This process iterates until the centroids stabilize, resulting in user segments. The result clustering of user data is shown in **Fig 2**.

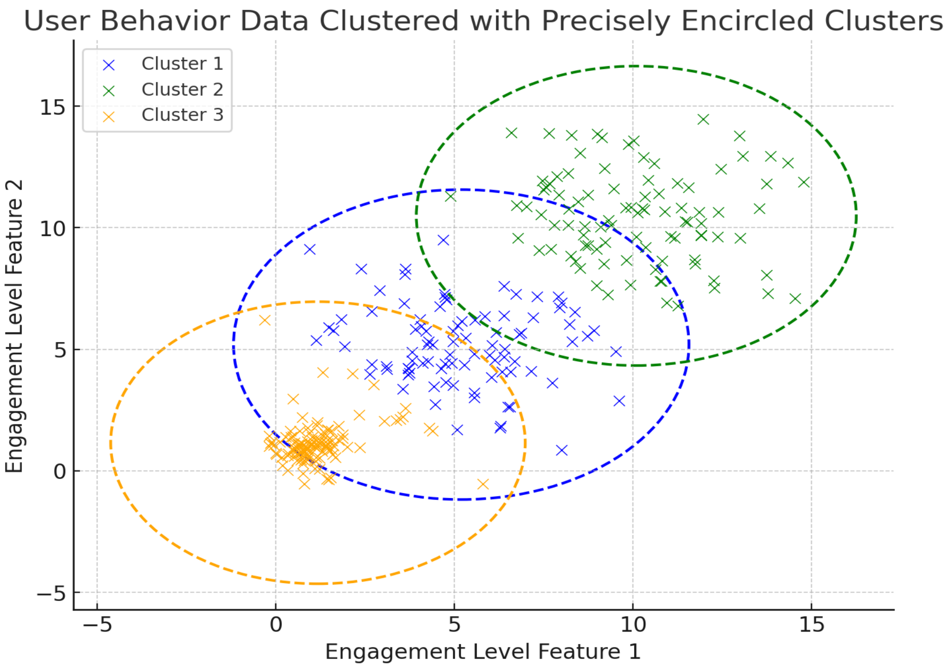

Fig 2. Clustering Of User Data.

Principal Component Analysis (PCA)

The PCA process is employed to reduce the dimension, it begins with standardizing the data to ensure each variable has a mean of zero and a standard deviation of one. After standardization, the covariance matrix Σ is computed to identify the relationships between all pairs of variables in the dataset, EQU (2).

$$\Sigma = \frac{1}{n-1} X^T X \tag{2}$$

where X is the standardized data matrix, and n is the number of observations. Next, the eigenvalues and eigenvectors of the covariance matrix are calculated, EQU (3).

$$\Sigma v = \lambda v \tag{3}$$

where λ represents the eigenvalues and v represents the eigenvectors.

The eigenvalues are then ranked in descending order and top-k components are selected which account for the majority of the variance in the data. The original data matrix X is then transformed into a new k-dimensional space defined by the selected principal components, EQU (4).

$$Y = XV_k \tag{4}$$

where V_k is the matrix of the top k eigenvectors. The following **Fig 3** show the PCA application on data.

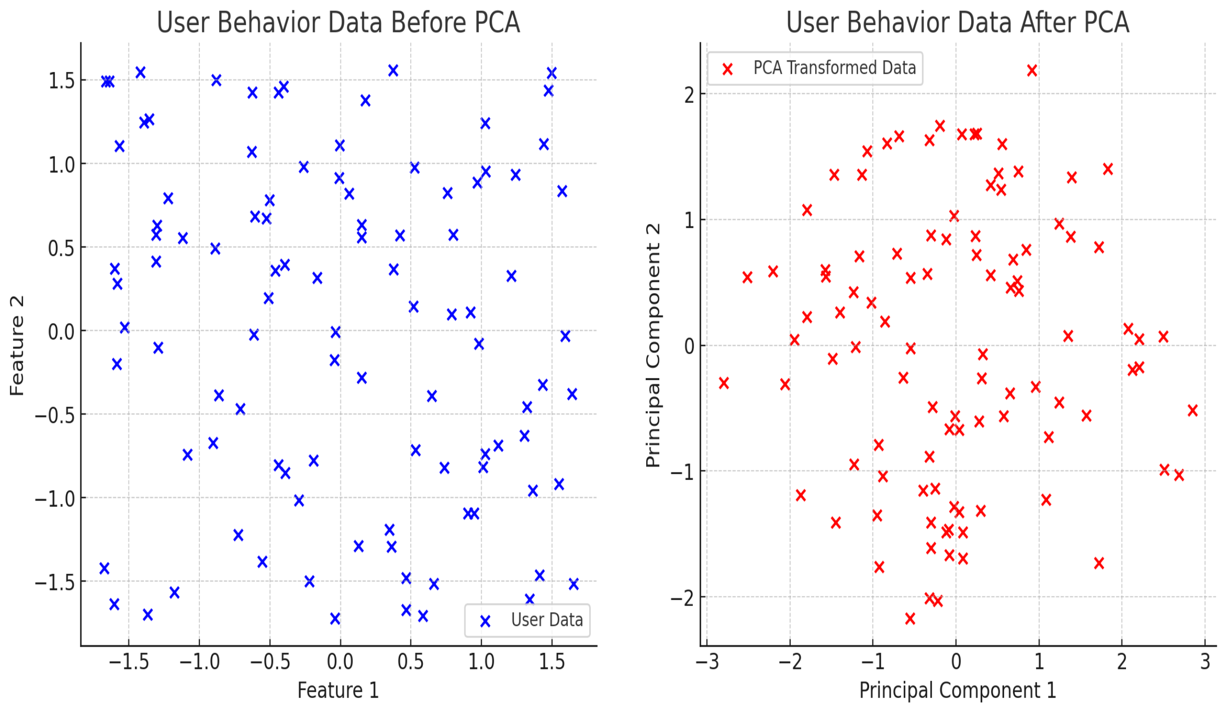

Fig 3. PCA Data Reduction.

Pattern Mining Using GSP

The GSP is employed to track and predict sequences of user actions, such as viewing products, adding items to carts, and completing purchases. The dataset comprises of user session logs from the e-commerce platform. Each session log details the sequence of actions performed by a user during their visit. The actions in each session are timestamped and ordered.

A minimum support threshold, *Min_Sup* is determined based on the dataset size and the variability of user behavior. Based on this threshold all individual actions are identified that meet the minimum support that result in L_1 a set of frequent single-action sequences. Next the longer sequences are iteratively generated by appending actions to the sequences from the previous ensuring each new sequence satisfies *Min_Sup*. Then each candidate sequence generated is validated against the dataset to calculate its support, EQU (5).

$$\text{Support}\ (s) = \frac{\text{Number of sessions containing } s}{\text{Total number of sessions}} \tag{5}$$

Only sequences with support exceeding *Min_Sup* is passed to the next iteration. This process continues, with sequences being extended and pruned based on their support. The iteration stops when no further extensions meet the *Min_Sup*. The frequent sequences identifies common pathways through the website and typical user actions leading to purchases.

Predicting Behavior Pattern Using DT

DT are employed to classify and predict the user behaviors. By building trees based on decision rules derived from user data, the users can be segmented and their future behaviors are forecasted. The Decision Tree algorithm identifies the best feature at each node to split the data based on the highest information gain, which is calculated using metrics like Gini impurity or entropy:

- Entropy for a set S is defined as EQU (6)

$$\text{Entropy}\ (S) = -\sum_{i=1}^{c} p_i \log_2 (p_i) \tag{6}$$

where p_i is the proportion of the number of elements in class i to the number of elements in set S, representing the randomness or impurity in the set.

- Gini Impurity for a set S is given by EQU (7).

$$\text{Gini}\ (S) = 1 - \sum_{i=1}^{c} p_i^2 \tag{7}$$

which measures the frequency at which any element of the dataset will be mislabeled when it is randomly labeled according to the distribution of labels in the dataset.

Recursive Splitting and Tree Growth

At each node, the algorithm splits the data into sub-nodes, choosing splits until the nodes are pure or until achieving a predefined depth to prevent overfitting, thereby maximizing information gain at each decision point.

Pruning the Tree

To avoid overfitting, pruning techniques like cost-complexity pruning are used where the tree is simplified by removing branches that have little impact on the classification accuracy. This is based on a complexity parameter and the change in the error rate:

- **Cost-Complexity Pruning:** Prune the tree by solving, EQU (8).

$$R_\alpha(T) = R(T) + \alpha|\tilde{T}| \quad (8)$$

where $R(T)$ is the total misclassification rate of the subtree T, $|\tilde{T}|$ is the number of terminal nodes in T, and α is the complexity parameter controlling the trade-off between tree size and its accuracy. The finalized DT classifies new user sessions into different categories such as potential buyers or likely cart abandoners. Analyzing paths that lead to successful outcomes enables the prediction of user preferences and identification of crucial decision points that influence user actions.

Next the LR is employed to integrate the GSP and DT output by modelling the probability of a binary outcome. The probability p of an event occurring is modeled using the logistic function, given by $p = \frac{1}{1+e^{-z}}$, where z is a linear combination of predictors: $z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$. Here, $\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients that the model will learn, and $x_1, x_2, \ldots, x_n$ are the features derived from the sequence patterns identified by GSP and the classifications provided by the DT. The features from GSP, are combined with classifications from the DT. This enhanced feature set is then used to train the LR model. The model is trained on a 80:20 split dataset comprising training and testing sets to evaluate its predictive performance effectively.

III. EXPERIMENT ANALYSIS

Statistical Analysis

Descriptive statistics as displayed in **Table 2** show moderate to high variability in engagement across different interaction types, with high averages for clicks on the homepage (150), scrolls on product pages (200), and views of product details (180). Chi-square tests in **Table 3** highlight significant relationships between demographics and engagement categories, such as age influencing overall clicks (Chi-square=12.5, p=0.014) and education affecting cart additions (Chi-square=15.2, p=0.009). These results indicate that demographic factors play a crucial role in shaping user behavior on the platform.

Pearson's correlation coefficients results as shown in **Table 4** reveal strong linear relationships between various interaction types, such as clicks and scroll depth on product pages (r=0.76, p<0.001) and item additions to cart vs. checkout process interactions (r=0.68, p<0.001). Linear regression analysis further identifies significant predictors of user engagement, with tech proficiency (coefficient=0.47, p<0.001) and education level (coefficient=0.40, p=0.001) showing strong predictive power. **Table 5** shows Linear Regression Analysis. **Fig 4** shows Descriptive Analysis. **Fig 5** shows Results for Inferential Analysis. **Fig 6** shows Linear Regression Analysis.

Table 2. Descriptive Analysis

Engagement Type	Mean	Standard Deviation
Clicks on Homepage	150	35
Scrolls on Product Page	200	50
Item Additions to Cart	75	20
Navigation through Categories	120	30
Views of Product Details	180	40
Checkout Process Interactions	90	25
Account Registrations	50	15
Video Views on Product Pages	110	33
Searches Conducted	160	45
Engagement with Promotional Content	140	38

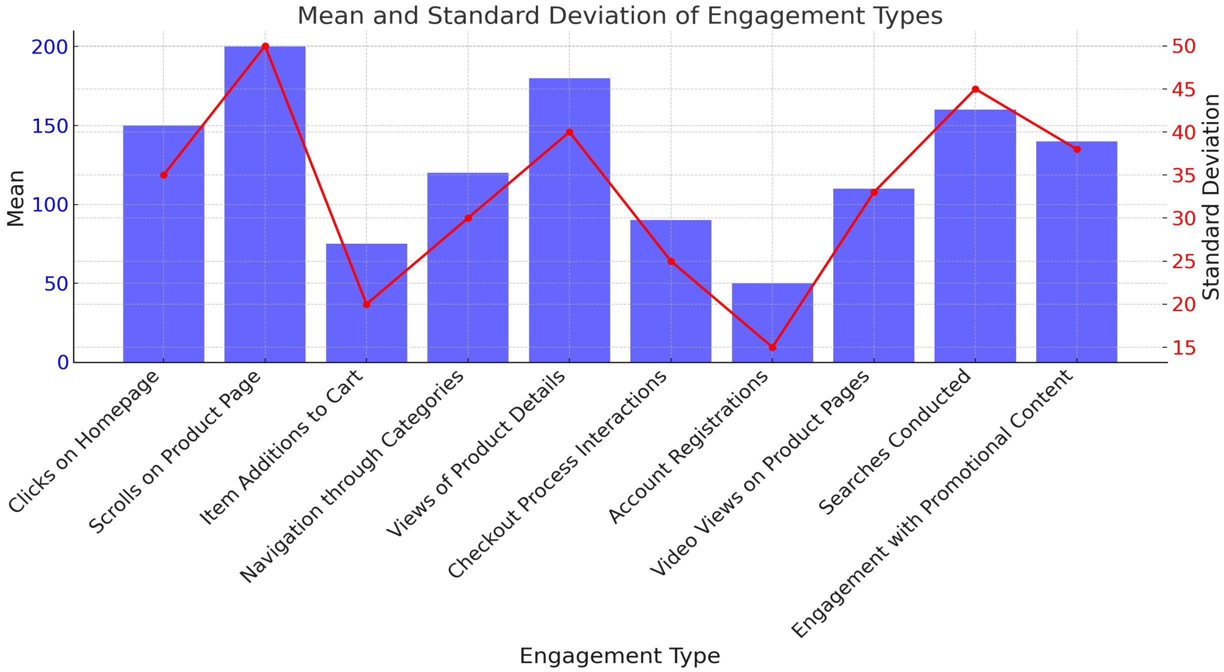

Fig 4. Descriptive Analysis.

Table 3. Inferential Analysis

Demographic vs. Engagement Category	Chi-Square Statistic	p-value
Age vs. Overall Clicks	12.5	0.014
Occupation vs. Overall Scrolls	9.8	0.032
Education vs. Cart Additions	15.2	0.009
Tech Proficiency vs. Category Navigation	11.3	0.023
Gender vs. Product Detail Views	10.6	0.030
Age vs. Checkout Interactions	13.7	0.010
Education vs. Account Registrations	8.5	0.045
Occupation vs. Video Engagement	14.1	0.008
Tech Proficiency vs. Search Activities	16.3	0.005
Gender vs. Promotional Engagement	12.9	0.012

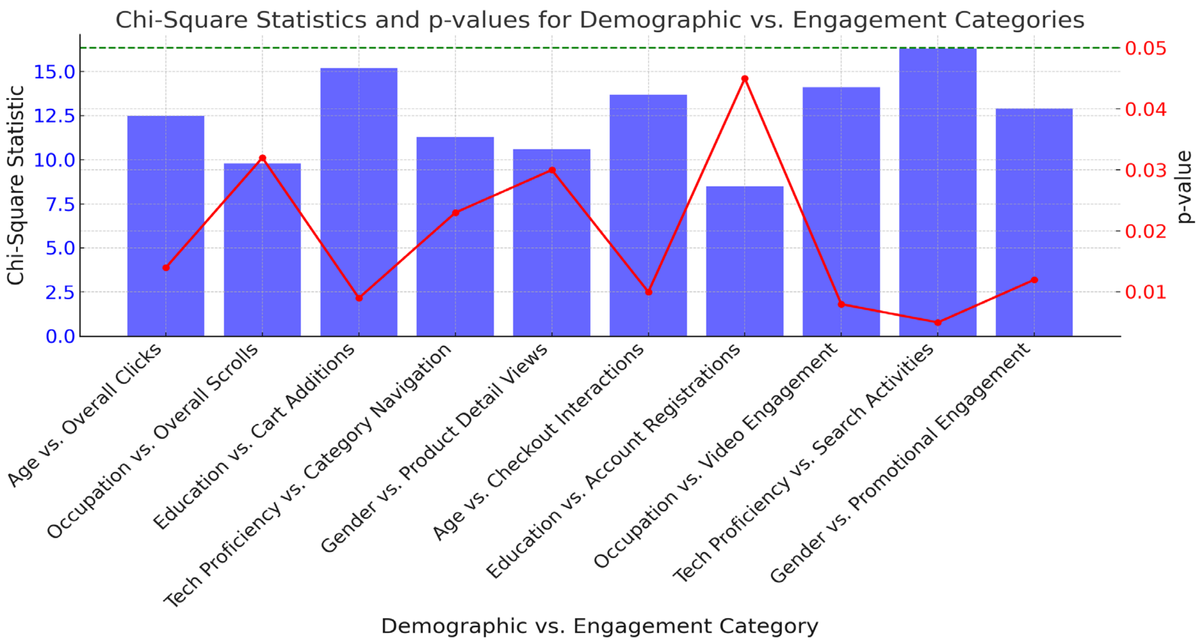

Fig 5. Results for Inferential Analysis.

Table 4. Pearson's Correlation Coefficient

Interaction Types	Correlation Coefficient	p-value
Clicks vs. Scroll Depth on Product Pages	0.76	< 0.001
Item Additions to Cart vs. Checkout Process Interactions	0.68	< 0.001
Views of Product Details vs. Engagement with Promotional Content	0.62	< 0.001
Navigation through Categories vs. Video Views on Product Pages	0.55	< 0.001
Searches Conducted vs. Clicks on Homepage	0.50	< 0.001

Table 5. Linear Regression Analysis

Predictor Variable	Regression Coefficient	Standard Error	p-value
Age	0.35	0.10	0.002
Tech Proficiency	0.47	0.12	< 0.001
Gender	0.25	0.09	0.015
Education Level	0.40	0.11	0.001
Occupation	0.30	0.10	0.004

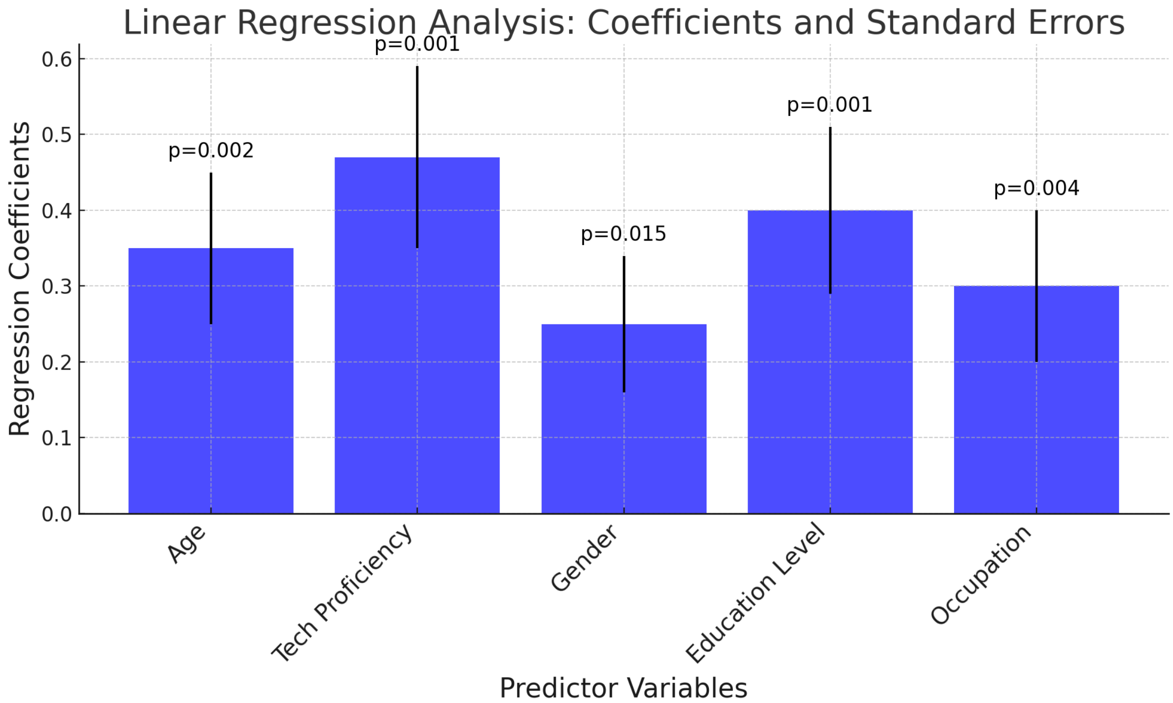

Fig 6. Linear Regression Analysis.

Machine Learning Analysis

The dataset was split into training and testing dataset in 80%:20% ratio. The proposed model is trained over the training dataset using the parameters as listed in **Table 6**. the model is compared with other baseline models such as DT, LR, RF and SVM. The models are compared against the metrics such as Accuracy, F1-score, AUC-ROC Precision and Recall.

Table 6. Training Parameters

Component	Parameter	Value
General	Data Split	80% Training, 20% Testing
DT	Max Depth	10
DT	Min Samples Split	2
LR	Learning Rate	0.01
LR	Epochs	100
LR	Batch Size	32
LR	Optimizer	Stochastic Gradient Descent (SGD)
LR	Loss Function	Cross-Entropy
General	Early Stopping	Enabled, patience=5 epochs

Table 7. Performance Comparison

Model	Dataset	Accuracy	F1 Score	AUC-ROC	Precision	Recall
Proposed Model	Training	0.9245	0.9032	0.9501	0.8931	0.9125
	Test	0.8795	0.8610	0.9103	0.8547	0.8712
DT	Training	0.9532	0.9274	0.9298	0.9156	0.9387
	Test	0.8031	0.7845	0.8192	0.7732	0.7968
LR	Training	0.8492	0.8305	0.8723	0.8221	0.8410
	Test	0.8157	0.7983	0.8534	0.7852	0.8106
SVM	Training	0.8998	0.8795	0.9204	0.8702	0.8867
	Test	0.8423	0.8210	0.8795	0.8125	0.8293
Random Forest	Training	0.9701	0.9503	0.9602	0.9445	0.9578
	Test	0.8576	0.8412	0.8889	0.8324	0.8505

The performance of the proposed model compared with other models are presented in **Table7**. The proposed model demonstrates better performance across all metrics on both datasets. During training, it achieves an accuracy of 0.9245, an F1-score of 0.9032, an AUC-ROC of 0.9501, a precision of 0.8931, and a recall of 0.9125. On the test dataset, the performance slightly decreases but remains strong, with an accuracy of 0.8795, an F1-score of 0.8610, an AUC-ROC of 0.9103, a precision of 0.8547, and a recall of 0.8712. This indicates that the proposed model generalizes well to unseen data, maintaining a good balance between precision and recall, and achieving a high AUC-ROC, which suggests good discrimination ability. The DT model shows a high training performance with an accuracy of 0.9532, and lower performance in test dataset with an accuracy of 0.8031, an F1 Score of 0.7845, an AUC-ROC of 0.8192, a precision of 0.7732, and a recall of 0.7968. The LR model shows consistent performance between the training and test datasets, with an accuracy of 0.8492 for training dataset and the accuracy of 0.8157 for test dataset. The SVM model achieved an accuracy of 0.8998, an F1 Score of 0.8795, an AUC-ROC of 0.9204, a precision of 0.8702, and a recall of 0.8867 for training dataset and an accuracy of 0.8423, an F1-score of 0.8210, an AUC-ROC of 0.8795, a precision of 0.8125, and a recall of 0.8293 for test dataset. The RF showed an accuracy of 0.9701 for training dataset and on the test dataset it achieved an accuracy of 0.8576.

Table 8: Conversion Rate and Bounce Rate

Model	Conversion Rate (%)	Bounce Rate (%)
Proposed Model	12.34	28.65
DT	10.12	35.43
LR	9.87	32.98
SVM	11.57	30.12
RF	10.98	33.45

Table 9. Computation Time Comparison

Model	Computation Time (seconds)
Proposed Model	189.75
DT	55.61
LR	40.73
SVM	155.57
RF	250.55

As shown in **Table 8**, the Proposed model achieves the highest conversion rate at 12.34% and the lowest bounce rate at 28.65%. The DT model, with a conversion rate of 10.12% and a bounce rate of 35.43%, shows moderate effectiveness. LR shows the lowest conversion rate at 9.87% and a bounce rate of 32.98%. The SVM model achieves a relatively high conversion rate of 11.57% and a bounce rate of 30.12%, and The RF model shows a conversion rate of 10.98% and a bounce rate of 33.45%, performing better than LR and DT. The **Table 9** displays the computations time for each compared model, the proposed model was one among the model with higher computation with time 189.75 seconds next to RF and SVM each having 250.55 and 155.57 seconds respectively. The LR model was the least intensive model with 40.73 seconds followed by DT model with 55.61 seconds.

IV. CONCLUSION

Enhancing user experience is an important factor to improve the sales and retainment of sales in e-commerce platforms. To develop an efficient UX model the user behavior must be accurately predicted so that to design any platform to generate user experience based on individual user behavior. This study is an attempt to tackle the limitations in existing models the proposed work employs advanced AI tools to predict user behavior so that to construct an more effective UX model. The study involved 80 users from China who were aged 26 to 52, with diverse backgrounds in education, occupation, and tech proficiency. The work have employed Google Analytics, Hotjar, and FullStory to collect the user interactions and by using Generalized Sequential Pattern (GSP) algorithm, Decision Trees, and Logistic Regression the work attempts to accurately predict the user behavior patterns. The results show that the model achieved better accuracy of 0.8795 and an F1-score of 0.8610 on the test dataset. It also excelled in conversion rate (12.34%) and bounce rate (28.65%) which show effectiveness in retaining users and converting visits into actions.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests

There are no competing interests.

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