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Quantifying the Impact of Psychological and User Experience Factors on Online Shopping Satisfaction Via Predictive Models

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Abstract - **This study examines the joint influence of psychological and user experience (UX) factors on online shopping satisfaction using predictive modelling. The importance of this research is to address a gap in previous e-commerce research, in which psychological drivers and UX attributes are usually analysed independently. Understanding the combined effect of them is crucial to designing customer-centric digital commerce environments. The research has gathered data from online shoppers in Coimbatore, India, using a structured questionnaire. A total of 238 responses were collected, and after data cleaning, 212 valid observations were kept for modelling. Psychological constructs, including trust, fear of missing out (FOMO), price sensitivity, social influence, and emotional motivation, were measured using multi-item Likert-scale questions adapted from the consumer behaviour literature. These responses were transformed into composite numerical features through aggregation and normalisation. The machine learning models used in the research were Random Forest, Gradient Boosting, LightGBM and ElasticNet. Class imbalance was addressed using K-Means SMOTE resampling. Model evaluation revealed that the Random Forest model performed best, with a Mean Absolute Error (MAE) of 0.379 and an R^2 of 0.179. Explainable AI analysis using SHAP values showed that approximately 1.5 times more of the prediction results were attributed to psychological factors than to UX features. These results show that internal psychological drivers are much more important than those related to the interface experienced to determine online shopping satisfaction. The research is a contribution to the field in that it combines behavioural theory, predictive modelling and explainable AI as an analytical framework. Future research can extend this framework to other geographic contexts and incorporate longitudinal behavioural data.**

Keywords: **Online Shopping, Psychological, User Experience, SHAP, Predictive Modelling, E-commerce**

I. INTRODUCTION

The growth of online shopping across the globe has led researchers to investigate the different factors that determine consumer satisfaction and their intentions to repurchase from an e-commerce site. Both psychological factors and user experience factors determine consumers' satisfaction, and such factors influence their behaviour. For instance, trust, social influence, and emotional motivation have been identified as the main psychological factors that influence consumers' satisfaction and intentions to repurchase products (Cuong, 2023). On the other hand, the personalisation recommendations moderate the relationship between trust, satisfaction, and loyalty among consumers in an AI environment in online shopping (Hassan et al., 2025).

In addition to the psychological factors, user experience factors play a critical role in influencing consumers' satisfaction when making purchases online. For this consumer, purchase behaviour after adding items to their carts is analysed (Esmeli & Gokce, 2025). The research highlights the importance of user experience factors in ensuring satisfaction. However, the integration of psychological and user experience factors in prediction models remains difficult, as previous studies have focused on analysing one factor at a time. Explainable Artificial Intelligence (XAI) is recommended as an effective tool to make sense of the interactions (Saranya & Subhashini, 2023).

The purpose of this study is to fill this gap through the use of predictive modelling alongside explainable AI, which will allow the assessment of both psychological and UX variables' joint effect on the satisfaction with online shopping experiences. This will not only contribute to the body of knowledge on consumer behaviour but will also provide practical recommendations on the approach that e-commerce websites should take in their interaction with users.

The key contributions of the paper are:

1. The paper proposes an innovative predictive model approach that considers both psychological and UX variables together to understand consumer satisfaction when shopping online, overcoming the problem of independent factor analysis prevalent in previous research.

2. The paper employs ensemble models of machine learning along with balancing methods for class imbalances in behavioural datasets.
3. The paper uses XAI (explainable artificial intelligence) via SHAP analysis to determine the contribution of psychological and UX variables to consumer satisfaction.
4. The paper demonstrates the preponderance of psychological variables over UX variables empirically in explaining consumer satisfaction with digital shopping experiences. The rest of this paper is organised as follows:

This paper is organised as follows: Section 1 presents the research question along with the importance of customer satisfaction in the field of e-commerce, and then the contribution of the research study is discussed. The theoretical framework and literature review on psychological and UX elements that influence e-shopping satisfaction are discussed in Section 2. In Section 3, the methodology adopted to conduct the study, including data gathering, feature selection, and ML algorithms, is discussed. The outcomes obtained from the experiments conducted are presented in Section 4. The outcomes are compared with earlier research in Section 5, where the role of psychological elements dominates. Finally, section 6 is the conclusion which summarises the statistical insights, the significance and the future study.

II. Theoretical Background and Literature Review

2.1 Literature Review

The development of consumer behaviour within the context of online retailing can be attributed to both psychological issues and user experience (UX) design issues. According to a study, there is an increasing need to examine how consumer purchasing behaviour changes, with special attention being paid to the aspect of online engagement as a key component of contemporary business operations (Liu, 2024). In addition to this, a work demonstrates the significance of developing frameworks that will allow one to study the concept of customer experience throughout its full course. It encompasses a number of touchpoints that influence consumer satisfaction and loyalty in e-commerce situations (Lemon & Verhoef, 2016).

This line of inquiry is enriched by examining the impact of trust on the interaction between online shopping variables and consumers' buying behaviour (Othman, 2021). Trust, along with risk perception and social influence, is identified as an important psychological variable that affects satisfaction and loyalty toward electronic commerce (Othman, 2021). In a complementary manner, a paper examined the dimensions of trust and its implications for technology adoption (McKnight et al., 2011)

Including XAI in such an analysis provides ways of interpreting the machine learning models, which can aid greatly in understanding the psychological and UX factors involved in consumer behaviour (Lundberg & Lee, 2017). The emphasis on providing transparency within AI-powered recommendations ensures that companies are able to give reasons why particular products are recommended to consumers (Lundberg & Lee, 2017). Such ideas are reflected in the recent studies, whose focus was on providing explanations for the predictions made by the classifier (Ribeiro et al., 2016).

Moreover, the psychological influences that affect the purchase decisions of consumers have been identified by a study (Mulyadi & Efawati, 2024). This paper suggests that variables such as FOMO and price sensitivity are essential in affecting consumers' decision-making process (Mulyadi & Efawati, 2024). According to a research paper, an excellent customer experience in the online space can be defined as the integration of psychological motivators and good user experience (Rose et al., 2012). While a study concentrated on the omnichannel digital approach to improve customer experience in developing countries, your work has the same aim but concentrates more on the psychological aspect using explainable artificial intelligence (Moreno-Menéndez et al., 2025).

In conclusion, it is vital to comprehend the relationship between psychological determinants and UX features for the prediction of consumers' behaviour during e-commerce. It is possible to enhance the satisfaction of users and customise their experience by considering psychological aspects and UX characteristics in tandem within machine learning algorithms and XAI. Therefore, further studies should be conducted on the correlation between these two variables, employing XAI (Chen et al., 2023; Zheng et al., 2017).

The most recent research has been centred around exploring the various determinants affecting customer satisfaction through the use of predictive analytics, machine learning, and XAI. Adopting big data through online customer review texts in predicting customer satisfaction in the hospitality industry, stressing the importance of customers' input in forming customer satisfaction indicators (Zhao et al., 2019). It is evident that such methods give the potential of using online customers' reviews in understanding consumer attitudes and satisfaction levels. Likewise, a study created a machine learning-based model of predicting purchases in e-commerce systems that highlighted the importance of the predictive nature of the models in predicting behaviour using past experiences. The study used various machine learning models to make predictions regarding future behaviour, which is essential in ensuring customer retention (Liu et al., 2020). This is supported by the study, which explored how beliefs about online stores could affect consumer impulse buying (Verhagen & Van Dolen, 2011).

The increasing importance of predictability through analytics in improving the consumer experience in the context of e-commerce is mentioned in a study (Asrafuzzaman et al., 2025). Through the application of machine learning and big data, organisations will be able to forecast consumer behaviour and customise their services to cater to individual consumers' needs, which will contribute to increased satisfaction and loyalty (Asrafuzzaman et al., 2025). The importance of explainability of AI models in improving customer experiences is examined, noting that transparency of AI solutions helps consumers understand the reasons for recommending certain products and purchases (Ansari et al., 2023).

Combined, these works indicate that machine learning, prediction, and AI explanations should be implemented in e-commerce platforms. With the combination of these modern approaches along with the conventional understanding of consumer behaviour, businesses will be able to learn more about their customers and build loyalty.

2.2 Inference

In the literature, it is noted that the influence of psychological and UX factors on customer satisfaction in online shopping plays an important role. Specifically, the psychological factors affect customer satisfaction directly, while the UX factors contribute to satisfaction indirectly. In general, the traditional models demonstrated poor predictive results, whereas the machine learning techniques helped to improve performance by considering nonlinear correlations. This research combines both psychological and UX factors in the model with the use of machine learning models and SHAP for interpretation.

2.3 Research Gap and Motivation

The gaps identified in the literature review for the research topic of online shopping satisfaction include three major ones. Firstly, there is no research that takes into account both psychological and UX variables within one predictive model. As a result, research findings are isolated from each other, and the relationship between the two factors and the overall level of customer satisfaction is not established properly. Secondly, most of the predictive models presented in the reviewed studies do not provide sufficient explanations on how different components influence the output. Thirdly, few studies focus on overcoming the problem of the class imbalance while trying to maintain high interpretability. The current study integrates feature-engineered psychological and UX indices with balanced predictive modelling and XAI techniques. Using this approach, the relative and hierarchical contributions of both factors influencing online shopping satisfaction can be assessed.

III. Methodological Framework

This research adopts a quantitative empirical research design, combining behavioural measurement surveys and predictive machine-learning analysis. The four key steps involved in the research process include data collection using a structured questionnaire, feature engineering of psychological and user experience constructs, predictive modelling with ensemble learning algorithms, and explainable results using SHAP values. The survey method was used because psychological constructs such as trust, emotional motivation, and social influence are latent behavioural variables that can be best measured using self-reported responses. Integration of behavioural survey data and predictive modelling enables the study to assess the statistical relationships and the predictive impact of various factors on online shopping satisfaction.

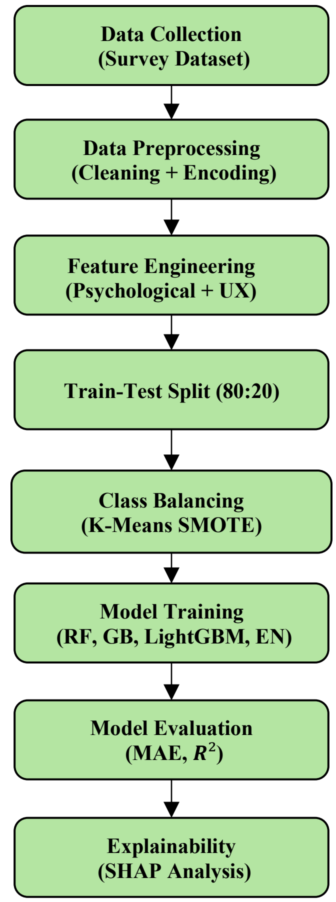

Fig. 1 Overall Methodological Workflow for Analysing Online Shopping Satisfaction Using Predictive Modelling and Explainable AI

3.1 Dataset Overview

A survey was administered through the Internet in order to collect data concerning different attributes, which include demographics like age, sex, monthly income, employment characteristics; psychological attributes like trust, comfort, price-sensitivity, emotion and cognition, and social-behavioural; user-experience attributes like customer service, web and application usability, information quality, transaction/logistics experience, and price-related issues. The target attribute indicates satisfaction with online shopping; an ordinal scale with 5 possible values was used, with 4 representing maximum satisfaction and 0 being the lowest level of satisfaction.

The sample was mostly working professionals and students (aged 18 to 45) who regularly shop online. Although convenience sampling was employed, the diversity in age, income level, and employment category helped ensure representativeness across major online consumer segments. The dataset contains numerical data, such as age and income, and categorical data, like gender and job type. In addition, there is ordinal data that consists of Likert scale measures for satisfaction and psychological reactions. The research employs a well-defined methodology that combines behavioural data obtained through surveys with predictive modelling and explainable artificial intelligence. The entire process flow in the suggested framework is shown in fig. 1.

A convenience sample is employed due to the limited accessibility and the exploratory approach of the research. The sample consisted of online shoppers aged between 18 to 45 years, who regularly engage with e-commerce sites. This particular demographic is one of the most frequent users of online commerce services within India. While the selected method does not guarantee that the sample will be representative of the overall population, convenience sampling allows for respondents with different job positions, salaries, and ages to be included, thereby accounting for variance in consumer behaviour. Fig. 1 presents the research design which involves several important steps: (i) data collection using structured survey tools, (ii) pre-processing and feature engineering of psychological and UX variables, (iii) addressing the class imbalance problem with K-Means SMOTE technique, (iv) prediction modeling using ensemble methods, (v) assessing the models with MAE and R^2, and (vi) analyzing feature contribution using SHAP.

3.1.1 Data Collection Procedure

In the research process, data were gathered from an online survey carried out from January to February 2025. The survey targeted individuals with previous experience in online shopping. The survey was carried out in Coimbatore (Tamil Nadu), India. The geographical region was selected because of the consistency of consumer behaviour in the emerging digital urban marketplace. The data was collected by distributing an online survey questionnaire that resulted in the collection of 238 responses. After preliminary screening and data cleaning, only 212 responses were retained for analysis. Data with incomplete and inconsistent responses were eliminated for quality purposes. A convenient sampling strategy was employed in the data collection process due to logistical issues. The respondents were working professionals and university students in the age bracket of 18 to 45 years old, who are active online shoppers interacting with online e-commerce websites. The online survey questionnaire was sent using Google Forms and shared on emails and social media platforms, including WhatsApp and Instagram. Survey participation was completely voluntary, and no monetary rewards were provided. All respondents were aware of the academic nature of the research prior to taking the survey. This method of gathering information was employed in order to gather a variety of views on the psychological and experience-related aspects affecting consumer satisfaction with online purchases.

3.2 Data Preprocessing

3.2.1 Data Cleaning

Prior to data encoding, data was checked for any missing values, inconsistent values and outliers. Questionnaire responses where there was an incomplete questionnaire are deleted from the data set. Small amounts of missing values, less than 5%, are filled using mean and mode imputation, based on variable type.

Identification of outliers is done using the Interquartile range method, and extreme values exceeding 1.5 Interquartile ranges were further investigated and eliminated if inconsistent. Duplicates were detected and deleted from the data set.

3.2.2 Exploratory Data Analysis and Feature Selection

Exploratory Data Analysis (EDA) was performed to learn the distribution of variables, correlations and class imbalance patterns. Correlation analysis and feature importance ranking were used to remove redundant variables. Highly correlated variables (correlation > 0.85) were checked for multicollinearity. Feature engineering techniques were used to combine similar survey items into composite psychological and UX indices.

3.2.3 Data Encoding

The data set includes both numerical and categorical values, which are encoded using one-hot, ordinal and binary encoding schemes

3.2.4 Psychological Feature Engineering

Psychological features were designed to represent the internal cognitive, emotional, and behavioural tendencies that affect satisfaction with online purchases. These constructs represent the consumer's perceptions of trust, risk, motivation, and social influence in online shopping interactions.

Measurement items were gathered based on a five-point Likert scale from 0 (Strongly Disagree) to 4 (Strongly Agree). The psychological constructs were adapted from validated constructs from e-commerce and consumer behaviour. The measures used for assessing trust and risk perception had their foundations in existing theories of online trust. However, the variables dealing with emotions and satisfaction were developed in light of past literature on the experience of consumers online. Newer research findings have corroborated the importance of the psychological aspects in AI-driven e-commerce environments.

The research took into account several important psychological constructs such as perceptions of trust and safety, fear of missing out, social proof, emotions, personal motivations, price sensitivity, and delivery dependability. These aspects are highly important in identifying the psychological mechanisms behind customer satisfaction with online shopping.

The constructs comprised multiple survey items, and composite psychological measures were computed based on averaging responses on Likert scales. Aggregation of variables reduces noise in addition to making the extracted psychological features more stable and representative of their underlying constructs.

Reliability checks of constructs comprising multiple items are conducted in the data preprocessing phase. Psychological scores obtained from the aggregation process were also standardised before being employed as features in machine learning algorithms. By translating subjective psychological responses into numeric values, the study integrates behavioural principles and computational models in predicting customer satisfaction.

3.2.5 User Experience (UX) Feature Engineering

UX features were developed from survey data that reflect how users interact with and experience the online shopping platform. These features capture perceptions related to ease of use, accessibility, and service efficiency. These factors include customer service experience, website and application usability, product information and presentation-related features, transaction and logistics experience, price comparison and transparency-related features. The features are created by applying a feature engineering process. Both psychological and UX features are normalised and aggregated to create standardised composite indicators. Overall shopping satisfaction is selected as the target attribute on a 0 to 4 scale.

3.2.6 Definition of Key Variables

The main variables to be used in the study are classified into three groups.

Psychological Variables

Psychological constructs define consumer satisfaction in terms of internal behavioural tendencies. These include trust perception, fear of missing out (FOMO), social influence, emotional motivation, perceived delivery reliability and price sensitivity. Each construct was measured using more than one Likert-scale statement, ranging from 0 (strongly disagree) to 4 (strongly agree).

User Experience Variables

User experience (UX) features describe the quality of the interaction between consumers and online shopping platforms. These variables can be website usability, quality of information, responsiveness of customer service, reliability of the platform, customer experience with logistics, and price transparency.

Target Variable

Overall satisfaction with online shopping was used as the dependent variable. It was assessed on a five-point ordinal scale from 0 (very dissatisfied) to 4 (very satisfied). This is the variable that is being estimated by the predictive models.

3.3 Balancing of Class Distribution

The dataset showed an imbalance since there is a clear dominance of the satisfaction level 3 category, and some categories were poorly represented. For accurate training of the models, all these categories are removed. Even after removing the rare categories from the dataset, the resulting data is imbalanced. To ensure unbiased evaluation, the dataset is first randomly divided into a training and a test set using an 80:20 split.

After this train-test split, class-imbalance correction was applied only to the training dataset. For main model training, Means-SMOTE was employed because of its ability to generate synthetic samples within a homogeneous cluster. Integration of K-means clustering with SMOTE-based oversampling will preserve the natural relationships among psychological and UX variables while reducing the influence of majority classes. This makes the training data more balanced and allows the model to learn patterns more effectively related to less-represented satisfaction levels.

Additionally, Borderline-SMOTE was used during the validation stage as a comparative resampling method, as K-Means-SMOTE focuses on generating synthetic samples near class boundaries. As a result, this approach enables evaluation of the model's robustness and sensitivity across alternative imbalance-handling techniques.

3.4 Predictive Modelling of Online Shopping Satisfaction

To assess the impact of psychological and UX factors on online shopping satisfaction, several machine-learning-based predictive models were built and evaluated. The selected models include Random Forest, Gradient Boosting Regressor, LightGBM, ElasticNet, etc., chosen for their strong ability to capture complex, non-linear relationships among input features and the target outcome, the overall satisfaction level. These ensemble-based algorithms are particularly well-suited for consumer behaviour analysis, where psychological and UX factors interact in complex, nonlinear ways.

All models were trained on the balanced training dataset (after KMeans SMOTE oversampling), and performance was evaluated on the hold-out test set using standard metrics, including Mean Absolute Error (MAE) and $R^{2.}$

To make the predictive models robust, validation procedures were applied during model training and evaluation. The data set was initially split into training and testing sets with an 80:20 ratio. Class-imbalance correction is implemented for the training dataset alone to avoid any potential information leak. Model performance is evaluated using MAE and R^2.

Moreover, other techniques like Borderline-SMOTE were examined to evaluate the sensitivity of model performance to the use of different techniques for class-imbalance correction.

3.5 Feature Contribution Analysis Using SHAP Values

In order to identify the most important drivers of customer satisfaction in online shopping, SHAP analysis of the predictive models was conducted. SHAP is a method that calculates the impact of individual features, offering a feature importance score.

A SHAP summary plot illustrates these findings. The data points in this chart depict feature values of individual observations. Red dots represent high feature values, while blue dots correspond to low feature values. Feature value placement on the X axis demonstrates the extent to which a feature positively or negatively impacts the prediction of customer satisfaction. This enables to gauge the effect of psychological and UX factors on our predictions.

3.6 Analysis of Psychological and UX Factor Influence

Analysis of the relative importance of psychological and UX characteristics for consumer satisfaction with online purchases can be done through explanatory analysis of the trained predictive model. In doing so, a single metric for assessing the contribution of individual features to the prediction generated by the model is obtained. In order to conduct such an analysis, features associated with psychological and UX variables were grouped together, and then the contributions of the groups were aggregated to determine the total influence of each group of factors on the prediction. A SHAP summary plot serves as a visualisation tool for presenting the findings.

3.7 Implementation Environment and Tools

The predictive modelling framework proposed is done in Python. Data preprocessing, feature engineering, and exploratory data analysis were performed using Pandas and NumPy libraries. Machine learning models, including Random Forest, Gradient Boosting, and ElasticNet, were developed using the Scikit-learn library, while LightGBM was implemented using the LightGBM framework.

Class-imbalance handling techniques such as K-Means, SMOTE, and Borderline-SMOTE were implemented using the Imbalanced-learn (imblearn) library. Model evaluation metrics, including Mean Absolute Error (MAE) and coefficient of determination (R^2), were computed using Scikit-learn evaluation functions.

For model interpretability, the SHAP (Shapley Additive exPlanations) library was used to analyse feature importance and quantify the contribution of psychological and UX factors. All experiments were conducted in a Jupyter Notebook environment. The experiments were conducted on a system with a standard computational configuration to ensure the reproducibility and scalability of the proposed framework.

3.8 Refine Personalisation with AI-Driven Recommendations

There are several examples of how AI-based personalisation and FOMO have helped boost customer engagement in real-life scenarios. For example, there was a 25% improvement in the conversion rate in the category of fashion on the XYZ e-commerce platform when FOMO-based prompts such as "Only 3 left in stock" and "Sale ends soon, hurry up!" were used. Furthermore, there was an improvement in customer retention of 15% in the electronics category when customers were provided with personalised recommendations based on AI technology.

3.9 Ethical Considerations

Although there is no denying the effectiveness of using psychological triggers, such as FOMO, and emotional triggers in enhancing user engagement, it would be necessary to take note of the ethical problems that may arise from the application of the psychological triggers. It is necessary for the platforms to avoid exploiting vulnerable consumers and manipulating them into making certain purchases. Platforms need to inform consumers about the use of AI-driven recommendations, and it would be wise to offer an opt-out option as well.

IV. RESULT ANALYSIS

All experimental results were obtained using a Python-based implementation, including Scikit-learn, LightGBM, and SHAP libraries, executed in a Jupyter Notebook environment.

4.1 Balancing of Class Distribution

The original class distribution shows a strong dominance of class 3 (Fig. 2), and the other classes contain few samples. Classes with insufficient samples were removed. The imbalance of the classes is still present in the dataset that has been left after the removal of rare classes of satisfaction (Fig. 3).

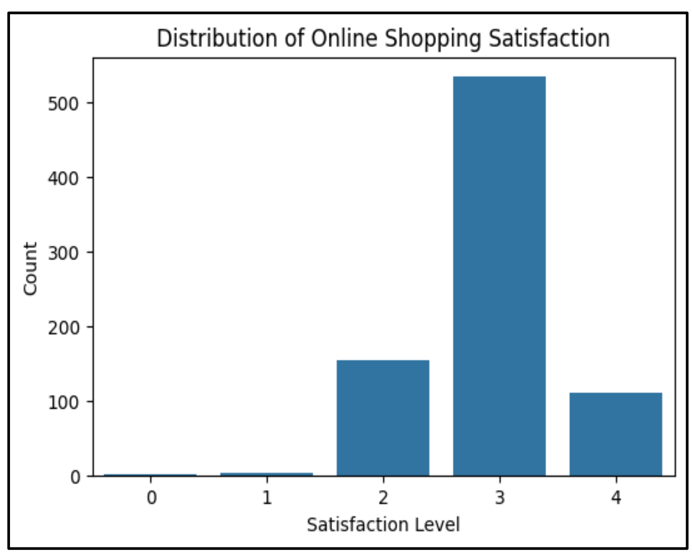

Fig. 2 Original Class Distribution of Online Shopping Satisfaction

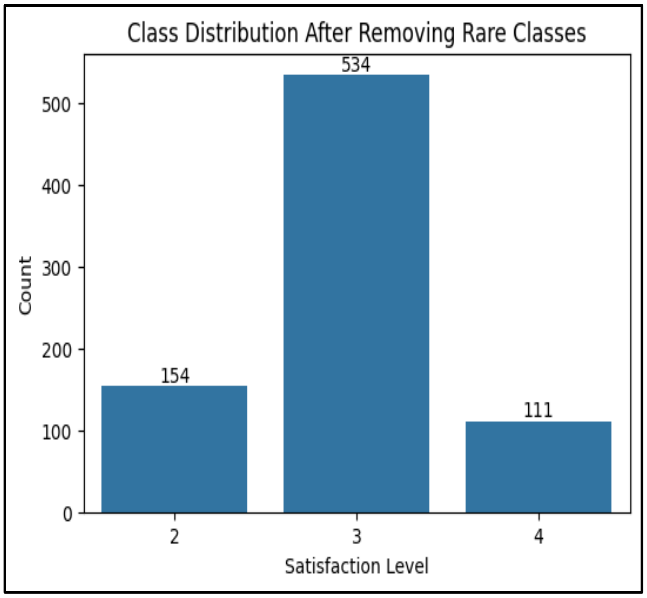

Fig. 3 Class Distribution After Minority Class Removal

4.2 Effect of Class Balancing on Training Data

Following the K-Means SMOTE oversampling technique, the class distribution for the training dataset was better balanced. This resulted in improved pattern learning from the data with respect to satisfaction levels that were underrepresented before. Class distribution before and after oversampling is presented in fig. 4 and 5.

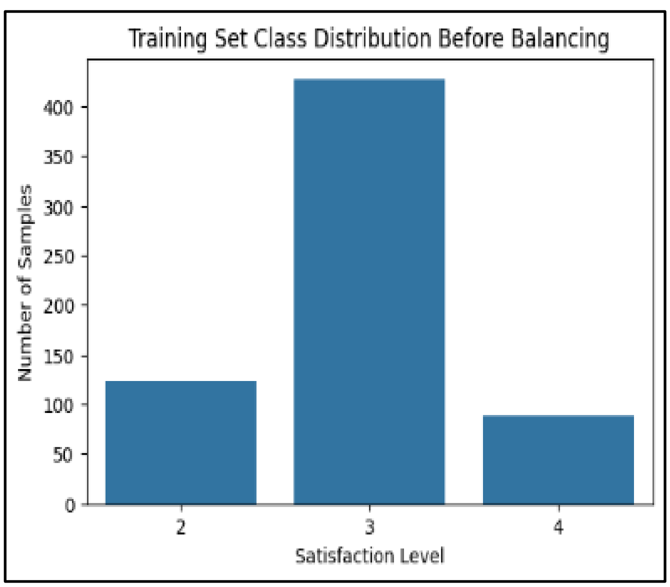

Fig. 4 Training Set Class Distribution Before Balancing

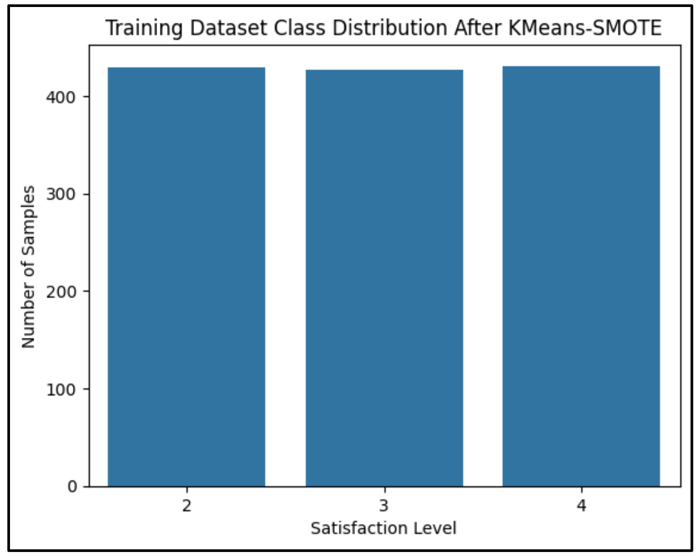

Fig. 5 Training Dataset Class Distribution After K-Means SMOTE

4.3 Comparative Impact of Resampling Techniques

Apart from K-Means SMOTE, the Borderline-SMOTE was also tested in the validation phase for comparative purposes. In terms of performance, the model is able to provide an MAE of 0.413 and an $R^2$of 0.073, showing average levels of predictive capability as shown in table I below. Despite using Borderline-SMOTE to improve class balance, a low level of R^2 implies weak predictive power.

TABLE I COMPARISON OF CLASS IMBALANCE HANDLING METHODS

Imbalance Handling Method	MAE	R^2
K-Means SMOTE	0.378	0.179
Borderline-SMOTE	0.413	0.073

4.4 Predictive Model Performance

Of all the models considered, the Random Forest model exhibits superior performance in terms of MAE (0.379) and R^2(0.179), suggesting that it has the highest predictive power and explanatory capabilities. While the performance of ensemble models is superior to that of linear models, this superiority can be attributed to the fact that ensemble methods have the capacity to learn complex and nonlinear relationships among psychological and UX variables. The high performance of gradient boosting, light gradient boosting, and extreme gradient boosting is further evidence that ensemble learning is effective in behavioural modelling.

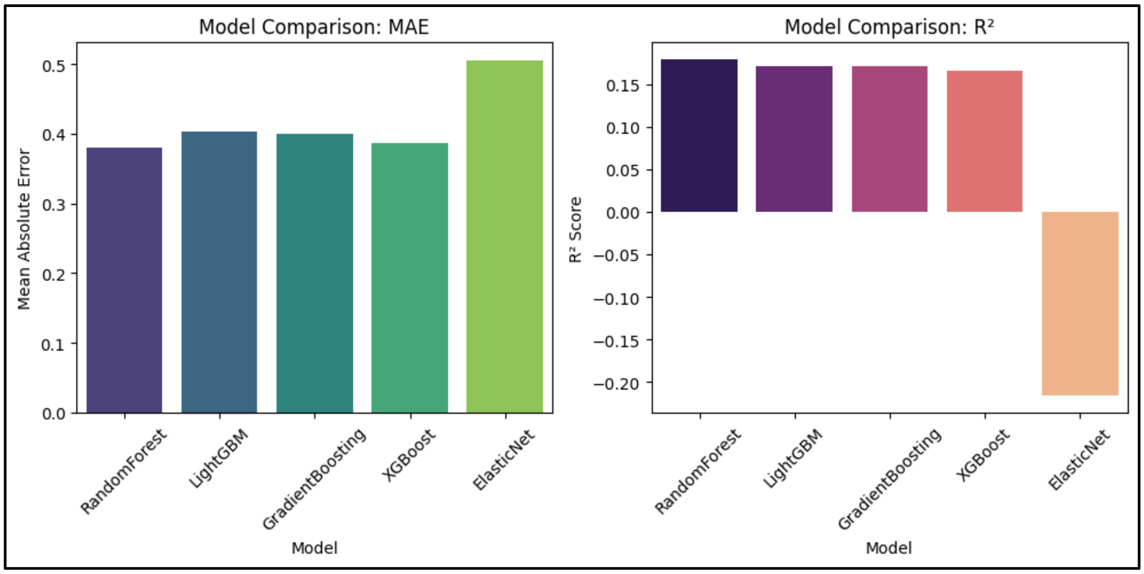

Fig. 6 Model Performance Comparison

The relative performance of various prediction models based on metrics like MAE and $R^2$is presented in fig. 6 below. In comparison with other prediction models, the Random Forest model performs excellently, with high explanatory capability and low prediction errors. Other models that perform well include the ensemble models (Gradient Boosting, LightGBM), although ElasticNet models exhibit relatively low accuracy.

TABLE II COMPARATIVE PERFORMANCE OF PREDICTIVE MODELS WITH LITERATURE REFERENCES

Model	MAE	R^2	Reference
RandomForest	0.379583	0.179446	(Lemon & Verhoef, 2016)
LightGBM	0.402356	0.171006	(Ribeiro et al., 2016)
GradientBoosting	0.399593	0.170894	(Lemon & Verhoef, 2016)
XGBoost	0.385855	0.166134	(Ribeiro et al., 2016)
ElasticNet	0.505607	-0.21653	(Lemon & Verhoef, 2016)

Table II presents the comparative performance of predictive models along with references to prior studies. The findings reveal that methods based on ensemble learning techniques exhibit superior performance compared to conventional modelling frameworks for predicting customer satisfaction. This is in agreement with prior studies. The use of several baseline models facilitates an assessment of the forecasting capability of the suggested framework.

The performance of various models is compared in fig. 6 based on Mean Absolute Error (MAE) and R^2 criteria. From the analysis, it can be observed that the Random Forest model performs the best since it gives the lowest value for MAE and the highest for R^2, which is an indicator of high accuracy and strength of the model's explanation. Other models like XGBoost, Gradient Boosting, and LightGBM also perform similarly, proving that they are effective in modelling the consumer's satisfaction with online shopping. However, it is clear from the results obtained that Elastic Net, which is a linear model, is inefficient for the purpose.

4.5 Feature Important Analysis

Fig. 7 shows the effect of SHAP values on model predictions. Most influential factors affecting online shopping satisfaction can be identified through SHAP analysis. The plot explains how each feature contributes to the model's predictions. Red plots indicate high features, and blue points indicate low values. The positions of points on the X-axis indicate whether they increase or decrease satisfaction.

The key insights of this research emphasis different aspects affecting satisfaction from online shopping. Monthly income and personal emotional aspects prove themselves as the strongest determinants, having significant power in defining customer satisfaction. In turn, age and promotions are characterised by moderate impact, implying that those aspects affect customer satisfaction, but their power is not comparable with that of others. UX-related aspects such as reliability of the service, its customer support, and security play an essential role in shaping the satisfaction rate, despite having less weight.

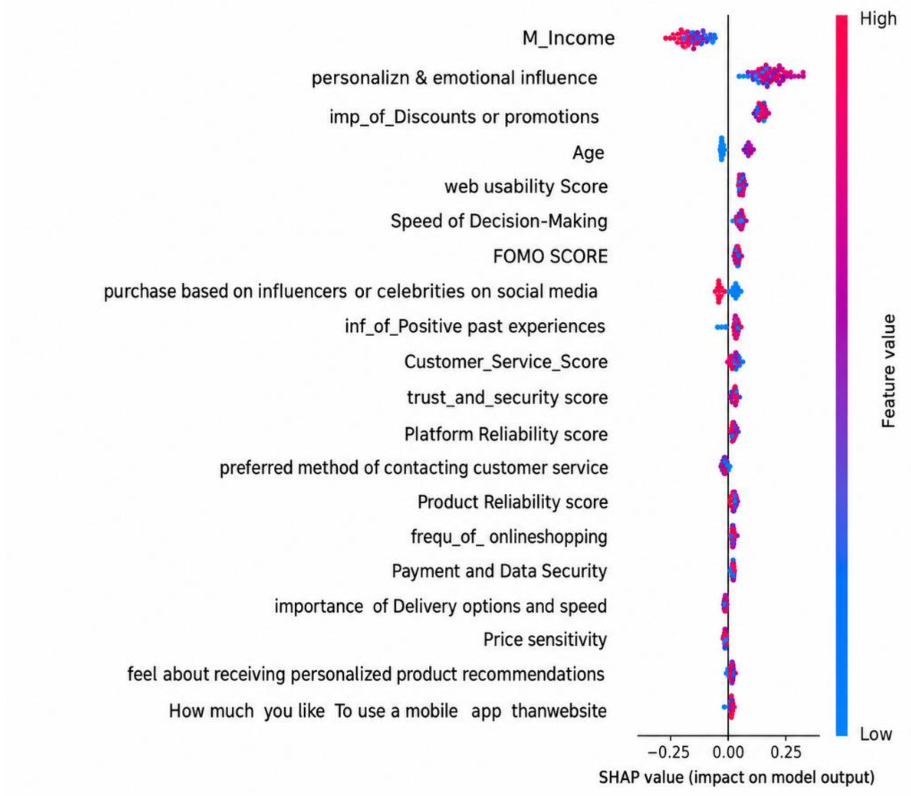

Fig. 7 Effect of SHAP Values on Model Predictions

4.6 Explanatory Analysis Results

Using the sum of mean absolute SHAP values, the relative influence of psychological factors compared to UX factors on online shopping satisfaction has been assessed. Fig. 8 compares the Influence of Psychological and UX feature contributions on online shopping satisfaction.

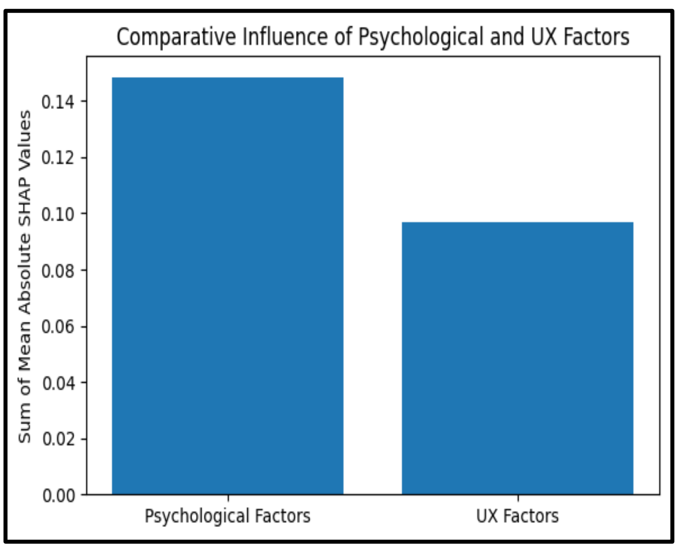

Fig. 8 Comparative Influence of Psychological and UX Feature Contribution to Online Shopping Satisfaction

Fig. 8 shows the impact of psychological factors on prediction results is much larger than the impact of UX factors. It can be seen from SHAP values that psychological attributes have an influence about 1.5 times more powerful. It can be concluded that psychological factors have a greater impact on the online shopping experience of consumers than UX factors due to the 1.5 times higher SHAP values. It means that consumer thoughts and attitudes toward products, including such characteristics as trust, fear of missing something good and social impact have more impact on consumers' online experience than any interface issues.

According to the research results, cognitive and emotional components are more important in influencing online shoppers' judgment about their online shopping experience than UX features. As opposed to prior research, which mostly concerns interface and usability issues of websites, it can be noted that behavioural drivers have greater predictive power.

V. Discussion

5.1 Comparison with Prior Work

Table III captures all the major differences between this proposed study and the previous work in the literature. This is because the new proposed model is unique in that it integrates psychological and UX features in order to develop the predictive model unlike previous works that only focus on one feature. Although the previous works have dealt with concepts such as customer satisfaction and personalization, the present study incorporates all these through the machine learning algorithms and XAI. The specific usage of SHAP in the paper makes it easier to gain insights into satisfaction during online shopping.

TABLE III COMPARISON OF THE PROPOSED STUDY WITH EXISTING LITERATURE

Study (Citation)	Focus Area	Methodology	Explainability	Key Limitation	Proposed Study Advantage
(Cuong, 2023)	Online shopping satisfaction & repurchase intention	Survey-based analysis of consumer satisfaction in Vietnam	Not included	Does not incorporate psychological & UX factors together	Integrates both psychological and UX factors in predictive modelling
(Hassan et al., 2025)	Trust-satisfaction-loyalty relationship in AI-driven e-commerce	Empirical study using AI-driven personalized recommendations	Not included	Limited to personalization impact	Explores joint impact of psychological factors and UX with explainable AI
(Esmeli & Gokce, 2025)	Consumer purchase behavior after cart addition	Predictive modelling using explainable AI	Uses explainable AI for purchase behavior analysis	Does not integrate psychological factors	Combines psychological factors with UX for a holistic model
(Liu, 2024)	Consumer buying behavior	Analysis of consumer buying patterns on online platforms	Not included	Limited to basic behavioral analysis	Utilizes SHAP and advanced machine learning for deeper insights
(Lemon & Verhoef, 2016)	Customer experience across the customer journey	Conceptual framework for customer experience management	Not included	General focus on customer journey without predictive modelling	Combines customer experience with psychological and UX analysis via ML

5.2 Discussion of Results and Implications

This result means that online shopping satisfaction is driven more by psychological aspects than the UX elements. In other words, a consumer's satisfaction with their online shopping experience is defined not only by what happens during it but also by their thoughts and feelings like trust, social influence, emotional motivation, and sense of security, rather than only through UX factors. While usability and visual design still matter, the influence of the latter on shoppers' satisfaction seems negligible in the absence of psychological drivers.

In addition, this result confirms findings from previous researches where the same psychological drivers, such as trust and perceived value, were considered key for people to engage in e-commerce. Previous research was mainly concentrated on website usability and service quality as factors affecting satisfaction. More recent behavioural analysis studies that used machine learning have proven the significance of psychological variables. Therefore, the current findings complement previous literature by demonstrating the greater contribution of psychological factors to predicting consumers' choices.

5.3 Practical Implications for E-Commerce Platforms

The implications of these findings for the e-commerce platform and digital business strategy include several critical recommendations. Firstly, the significant impact of psychological determinants, like trust, emotional motivation, and social influence, implies the need to focus on establishing customers' trust in a company. This may be done via adopting transparent rules, developing robust payment solutions, and delivering goods timely. Such aspects as user reviews and rating system will play a crucial role in increasing trust and reducing uncertainty in purchases.

Secondly, personalized engagement strategies, which can rely on using the power of FOMO and emotions, will make it possible to create products tailored to users' needs. Such tactics will help enhance customer satisfaction.

Thirdly, despite UX factors having relatively low weight compared to psychological ones, their importance should not be overlooked as supporting tools. Easy navigation, good customer support, and detailed information on products ensure efficient shopping and enhance customer satisfaction in connection with psychological engagement.

Finally, applying explainable AI methods, like SHAP, will help business stakeholders to understand the nature of factors influencing customer satisfaction and develop data-driven approaches to optimizing customer behaviour and system operation.

5.4 Limitations of the Study

In spite of its benefits, this research is subject to a number of limitations. First, the data used is obtained by means of convenience sampling in a particular region, which could reduce the validity of results in terms of their generalization to larger groups of respondents or application in other countries. Secondly, the reliance on the data provided by means of questionnaire surveys does not ensure complete objectivity, as people’s perceptions and habits might differ from their actual shopping behavior. The use of transactional data could increase the credibility of behavioral analysis in future studies. Lastly, while numerous machine learning algorithms were tested, only ensemble models were considered for predicting consumers' choices. Moreover, no attempt was made to apply deep learning networks, which would further boost the prediction power on large data sets.

Despite the many benefits when psychological triggers and AI recommendations within e-commerce are applied, there are some challenges that have to be addressed before any success can be achieved. Challenge 1: Establishing Trust: The level of trust will differ from one user to another depending on the cultural, geographical, and individual factors involved. This challenge could be addressed by ensuring that all e-commerce sites are able to offer multilingual and local payment methods, as well as social proof from influencers who are relevant to the situation.

VI. CONCLUSION

In this research, the study applied an explainable prediction and modelling framework to assess how psychology and user experience drive satisfaction in online shopping environments. Synthetic behavioural features were derived from survey responses among current online shoppers and assessed using ensembles of machine learning algorithms. The best prediction results are obtained with the Random Forest algorithm where MAE is equal to 0.379 and R^2 is 0.179, which indicates high efficiency of ensemble machine learning. It can be stated that psychological predictors are more influential in the process of shaping satisfaction when compared to other UX attributes. In particular, the results demonstrate that such psychological features as trust perception, motivation, and social aspects matter much more than such UX factors as usability or platform attributes. SHAP-based analysis demonstrated that psychological features explain about 1.5 times more predictions than UX variables. Thus, it becomes clear that behavioural considerations should be included into the digital commerce strategy. Online stores could improve their customers' satisfaction by improving trust mechanisms, social signals, etc.

Future studies can build upon this study's theoretical model by conducting empirical studies on bigger databases from multiple regions, including transactional records, and examining the way that psychosocial effects change with time. This can be achieved through the application of behavioral data for an extended period of time in future studies. In fact, the inclusion of behavioral data and the use of deep learning algorithms may be efficient in enhancing prediction accuracy. Moreover, the incorporation of sentiment analysis based on customer reviews and feedback can help understand the determinants of customer satisfaction, hence increasing the effectiveness of the model. Lastly, the scope of the research can be broadened through the inclusion of other sectors in online retailing such as fashion, electronics, and grocery industries.

REFERENCES

[1] Ansari, M., Ali, S. A., Alam, M., Chaudhary, K., & Rakshit, S. (2023). Unlocking the power of explainable AI to improve customer experiences in E-Commerce. In *AI-Based Data Analytics* (pp. 31-48). Auerbach Publications. https://doi.org/10.1201/9781032614083-3

[2] Asrafuzzaman, M., Hasan, M. T., Alam, M. K., & George, M. Z. H. (2025). Artificial Intelligence for Business Innovation: Revolutionizing Financial Analytics and Customer Modeling in Online Commerce. *Voice of the Publisher, 11,* 393-411. https://doi.org/10.4236/vp.2025.113028

[3] Chen, Y., Liu, H., Wen, Z., & Lin, W. (2023). How explainable machine learning enhances intelligence in explaining consumer purchase behavior: A random forest model with anchoring effects. *Systems*, *11*(6), 312. https://doi.org/10.3390/systems11060312

[4] Cuong, D. T. (2023). Determinants affecting online shopping consumers' satisfaction and repurchase intention: Evidence from Vietnam. *Innovative Marketing*, *19*(1), 126-139. http://dx.doi.org/10.21511/im.19(1).2023.11

[5] Esmeli, R., & Gokce, A. (2025). An analysis of consumer purchase behavior following cart addition in e-commerce utilizing explainable artificial intelligence. *Journal of Theoretical and Applied Electronic Commerce Research*, *20*(1), 28. https://doi.org/10.3390/jtaer20010028

[6] Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: an empirical study of AI-driven e-commerce. *Future Business Journal*, *11*(1), 66. https://doi.org/10.1186/s43093-025-00476-z

[7] Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of marketing*, *80*(6), 69-96. https://doi.org/10.1509/jm.15.0420

[8] Liu, C. J., Huang, T. S., Ho, P. T., Huang, J. C., & Hsieh, C. T. (2020). Machine learning-based e-commerce platform repurchase customer prediction model. *Plos one*, *15*(12), e0243105. https://doi.org/10.1371/journal.pone.0243105

[9] Liu, Z. (2024). Transformations in Consumer Buying Behavior: Investigating How Online Shopping Platforms. *Advances in Economics, Management and Political Sciences*, *109*(1), 181-186. https://doi.org/10.54254/2754-1169/109/2024BJ0135

[10] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, *30*. https://doi.org/10.48550/arXiv.1705.07874

[11] Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on management information systems (TMIS)*, *2*(2), 1-25. https://doi.org/10.1145/1985347.1985353

[12] Moreno-Menéndez, F. M., Zacarías-Rodríguez, V. E., Zacarías-Vallejos, S. R., González-Prida, V., Torres-Quillatupa, P. E., Romero-Girón, H., ... & Huaynate-Espejo, L. Á. (2025). Enhancing customer quality of experience through omnichannel digital strategies: Evidence from a service environment in an emerging context. *Future Internet*, *17*(6), 240. https://doi.org/10.3390/fi17060240

[13] Mulyadi, R. D. R., & Efawati, Y. (2024). Understanding Consumer Minds: How Psychological Aspects Drive E-commerce Purchases. *International Journal Administration, Business & Organization*, *5*(3), 15-23. https://doi.org/10.61242/ijabo.24.359

[14] Othman, A. K. (2021). The mediating role of customer trust in affecting the relationship between online shopping factors and customer purchase decision. *Journal of Information Technology Management*, *13*(3), 141-159. https://doi.org/10.22059/jitm.2021.83234

[15] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016, August). " Why should i trust you?" Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 1135-1144). https://doi.org/10.1145/2939672.2939778

[16] Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: an empirical model of antecedents and outcomes. *Journal of retailing*, *88*(2), 308-322. https://doi.org/10.1016/j.jretai.2012.03.001

[17] Saranya, A., & Subhashini, R. (2023). A systematic review of Explainable Artificial Intelligence models and applications: Recent developments and future trends. *Decision analytics journal*, *7*, 100230. https://doi.org/10.1016/j.dajour.2023.100230

[18] Verhagen, T., & Van Dolen, W. (2011). The influence of online store beliefs on consumer online impulse buying: A model and empirical application. *Information & management*, *48*(8), 320-327. https://doi.org/10.1016/j.im.2011.08.001

[19] Zhao, Y., Xu, X., & Wang, M. (2019). Predicting overall customer satisfaction: Big data evidence from hotel online textual reviews. *International journal of hospitality management*, *76*, 111-121. https://doi.org/10.1016/j.ijhm.2018.03.017

[20] Zheng, C., Yu, X., & Jin, Q. (2017). How user relationships affect user perceived value propositions of enterprises on social commerce platforms. *Information Systems Frontiers*, *19*(6), 1261-1271. https://doi.org/10.1007/s10796-017-9766-y