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Predicting the Customer Purchase Intention Based on Perception of Risk Using Machine Learning Techniques

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ABSTRACT

Online shopping has become an indispensable aspect of modern life. Nevertheless, this convenience is not without its risks. Potential pitfalls include fraudulent activity, subpar product quality, and the security of personal and financial information. The purpose of this research paper is to predict how individuals react in terms of online purchase intention, guided by their unique risk perceptions. It also aims to explore important risks and sociodemographic factors influencing the levels of perceived risk. This investigation was conducted through a survey questionnaire administered to a sample of 308 participants from India. Various machine learning models were applied to predict the customer purchase intention based on the various risks. The results revealed that the CatBoost Classifier outperformed the other methods. Following closely, Random Forest and Gradient Boost Classifier also demonstrated strong performance. By utilizing Random Forest's feature importance, factors such as financial risk, delivery risk, perceived health risk, time loss risk, and cultural risk significantly impact purchase intention. Additionally, among demographic factors, occupation has the most significant influence. This prediction model will offer practical insights for e-commerce platforms, marketers, and policymakers, enabling them to tailor strategies.

Keywords: Online Purchase Intention, Perceived risk, Machine Learning, Classifiers, Bagging and Boosting Models

1. INTRODUCTION

Although online shopping has grown in popularity over the years due to its convenience, it also carries a level of risk. Moreover, consumers may feel uneasy about the safety and security of their personal information and the quality of the products they are buying, which influence their purchasing decisions. This perceived risk can have a significant impact on consumer intention when it comes to online purchasing. In the dynamic landscape of e-commerce and digital marketplaces, understanding and accurately predicting customer behavior is pivotal for businesses striving to stay competitive. One of the critical factors influencing consumers' decision-making processes is their perception of risk associated with online transactions. As technology continues to evolve, so does the complexity of consumer decision-making, making it imperative for businesses to leverage advanced analytical tools. Consumer behavior in the digital era is characterized by a multitude of factors, with risk perception emerging as a central element in shaping purchase intentions. The perceived risks, such as financial, privacy, and performance-related concerns, significantly influence the decision-making process and act as barriers or facilitators in completing a transaction. Traditional approaches to understand consumer behavior often fall short in capturing the intricate and dynamic nature of risk perception. The convenience and accessibility of online shopping has propelled it to the forefront of modern retail, offering consumers a vast array of products and services at their fingertips. However, as online transactions have proliferated, so too have the complexities surrounding consumer choices and purchase intentions.

The integration of machine learning techniques in predicting customer purchase intention offers a unique advantage by enabling the analysis of vast datasets, uncovering patterns, and identifying non-linear relationships that may elude conventional analytical methods. By leveraging sophisticated algorithms, this research seeks to create a robust predictive framework capable of discerning the multifaceted dimensions of risk perception and translating them into actionable insights for businesses. By shedding light on the intricate connections between risk perception and purchase intention, businesses can refine their marketing strategies, bolster customer satisfaction, and fortify their competitive edge in the ever-evolving digital marketplace.

Through an extensive examination of existing literature, the current research on purchase intention has identified several gaps. Firstly, research has revealed new risks such as reputation and cultural risk that have not been extensively studied before. It would be beneficial to investigate the impact of these risks on purchase intention in greater depth. Secondly, most of the existing research has been conducted outside India, and so conducting such a study in our country would enable us to identify the specific factors that may impact purchase intention in the Indian context. Thirdly, to predict the consumer intention, machine learning techniques have not been applied on the perception of risk and so it aims to bridge this gap by harnessing the power of machine learning algorithms to develop predictive models that can effectively anticipate customer purchase intentions in the context of perceived risks. The prediction has been done on real data which makes it more authentic and trustworthy.

The objective of this study is to predict how individuals react in terms of online purchase intention, guided by their unique risk perceptions, and is an inquiry of paramount importance. This research endeavors to delve into the intricate web of consumer behavior within the digital shopping realm by examining how individuals react based on their risk perception profiles. Employing advanced analytical techniques, we predict consumers intentions based on their risk perception profiles. Predicting consumers purchase intentions, we gain deeper insights into the interplay between risk perception and online purchase intentions, ultimately providing valuable guidance for e-commerce stakeholders. This prediction model will serve as a foundation for understanding how different risk perceptions influence online purchase intentions.

This paper is organized as follows. Literature Review is discussed in Section 2. Section 3 describes the research methodology followed in processing the data and analysing it. The results of the analysis is Section 4. Section 5 is the conclusion.

2. LITERATURE REVIEW

Numerous e-commerce studies have extensively explored the concepts of perceived risk and the intention to purchase online. Perceived risk is characterized by the extent to which consumers feel uncertain and concerned about potential negative outcomes associated with a specific product or service. The actions undertaken by customers during online purchases of goods or services collectively fall under the umbrella of online shopping intentions. Among these behaviors, the consumer's intent to make a purchase stands out as a significant aspect, and this intention is markedly shaped by various factors, prominently including the consumer's perception of risk.

2.1 Online Purchase Intention

The concept denoting the strength of a client's determination to engage in online purchasing is commonly referred to as consumer online purchase intention (Salisbury et al., 2001). Meskaran et al. (2013) define it as the customer's preparedness to acquire goods/services online through the internet. Moreover, Iqbal et al. (2012) characterize it as consumers' willingness to use online services, make actual purchases, or compare product prices. In essence, online purchase intention involves predicting actual buying actions by customers. Pavlou (2003), in analyzing online consumer behavior, identifies the likelihood of making an online purchase as a more dependable predictor of website visits.

The advantages of online shopping have become evident, offering consumers added convenience and expanded choices. Forster and Tang (2005) emphasize its role as an alternative during disasters, while Chauhan and Shah (2020) note its heightened preference during the COVID-19 pandemic to avoid risks associated with offline purchases. Factors influencing the reliability of online resources include the security of customer personal information, timely order receipt, and responsive customer service (Parasuraman, Zeithaml, & Berry, 1988; Kim, Lee, Han, & Lee, 2002; Janda, Trocchia, & Gwinner, 2002).

Despite these benefits, it is essential to scrutinize the drawbacks associated with online shopping. This highlights the importance of examining the disadvantages, harms, and risks linked to the concept. Zhang et al. (2002) assert that risks associated with online shopping significantly impact consumer buying behavior potentially leading consumers to abstain from online purchases if perceived risks exist. Consequently, scholars have explored the concept of perceived risks in online purchasing and its influence on the likelihood of completing a purchase.

2.2 Perceived Risk

Bauer (1960) was the pioneer in introducing the concept of perceived risk to the literature on consumer behavior. Perceived risk is defined as the buyer's uncertainty when acquiring items. Dowling and Staelin (1994) elaborate, describing it as "the consumer's perception of the uncertainty and adverse consequences of buying a product or service." The perception of risk during a purchase is inherently subjective for consumers, and this uncertainty can significantly influence their decision-making. The relationship between a person's perceptions, attitude, and intention to make an online purchase is strong and inversely correlated.

Bauer (1960) and Cox and Rich (1967) proposed that perceived risk comprises of two key components: consequences, representing the potential magnitude of loss, and uncertainty, indicating the likelihood of unfavorable outcomes. As users become aware of higher risks, their likelihood of purchasing goods diminishes (Roselius, 1971; Taylor, 1974).

Within the realm of information system research, perceived risk is now being explored from various perspectives. Technology adoption specialists increasingly recognize it as a multidimensional concept crucial in the adoption and acceptance of new technologies. This study delves into the diverse facets of risk perceptions associated with online purchasing and investigates their impact on consumers' intentions to make a purchase (e.g., Alrawad et al., 2023; Alkhawaldeh, 2023).

2.3 Using Machine Learning Techniques on Predicting Consumer Purchase Intention Using Perception of Risk

Machine learning (ML) is a type of artificial intelligence (AI) that allows computers to learn without being explicitly programmed. ML algorithms can be used to analyze large datasets of customer data to identify patterns and relationships that can be used to predict customer purchase intention.

Several studies have used ML to predict customer purchase intention using perception of risk. A study by Rusli, Zulkifle et al (2023) used six machine learning classification models, including Naïve Bayes, Random Forest, etc. on the dataset to identify a suitable model for predicting customer behavior. Several studies have leveraged various models and techniques to predict customer behavior in different contexts. Mandilas (2013) used the Technology Acceptance Model (TAM) to predict consumers' intentions to shop online based on perceived risk, usefulness, ease of use, enjoyment, internet usage, and demographics. A combination of multiple classifiers was used by E Kim et al. (2003) to predict customer purchase behavior. Logistic Regression, Neural Network, Maximum Entropy, and Naïve Bayes were applied to predict customer behavior (A. Mauser et al., 2004).

K. Maheswari et al.(2017) used an SVM algorithm to predict customer behavior in online shopping, considering factors such as quality, motivation, occupation and income level, perception, psychological, personality, reference groups, and demographic reasons, along with learning, beliefs, attitude, culture, and social forces. T D Quynh et al.(2017) focused on a vehicle coupon recommendation system to predict customer behavior using various classifiers like Decision tree, Random forest, Adaboost, XGBoost , SVC and others. The accuracy of results ranged from 68% to 76%. W Etaiwi et al.(2017) used classification algorithms (Naïve Bayes and SVM) which were evaluated for predicting banking customer behavior under the Apache Spark Data Processing System. The results showed that Naive Bayes(NB) prediction approach is more efficient than SVM in terms of precision, recall and F-measure. They also concluded that multi-class classifiers are more efficient than binary classifiers for prediction problems.

Rahman and Khan(2018) employed classification techniques to assess customer behavior in the banking sector based on credit, housing loan, personal loan, and demographics. Artificial Neural Network(ANN) worked best among all the models. Valecha et al. (2018) used random forest algorithm to predict customer purchase intention for mobile apps. The study found that the random forest algorithm was able to achieve an accuracy of 90% in predicting customer purchase intention. Jing Li et al.(2019) focused on machine learning-based methods which was used to predict customer behavior by considering different promotion techniques. Decision tree, cluster analysis, and Naïve Bayes were the ML models applied to analyze the behaviour.

N Hicham and S Karim(2022) utilized Discriminant Analysis (LDA), Naive Bayes (NB), Ada Boost Classifier, Support Vector Machines (SVM), CatBoost Classifier, and K-nearest neighbor (KNN) to predict customer behavior in the food industry using structured data. The results reveal that CatBoost Classifier outperforms the major homogenous classification approaches in terms of accuracy. Another study by F Safara(2022) during the COVID-19 pandemic used Support Vector Machine (SVM), Decision Tree (DT), Sequential Minimal Optimization (SMO), Artificial Neural Network (ANN), and Naïve Bayes (NB) to predict consumer behavior based on COVID data. Study revealed that Decision tree achieved the best result of 94.6% accuracy.

These studies suggest that ML can be an effective tool for predicting customer purchase intention using perception of risk. However, it is important to note that the accuracy of ML models depend on the quality of the data used to train the models.

3. RESEARCH METHODOLOGY

This section deals with the research method applied to predict the customer purchase intention. Data is first collected, then pre-processed and ML models applied to the processed data. The models are evaluated and then results of models compared to decide on the best model. Figure 1 shows the various steps carried out in conducting the research.

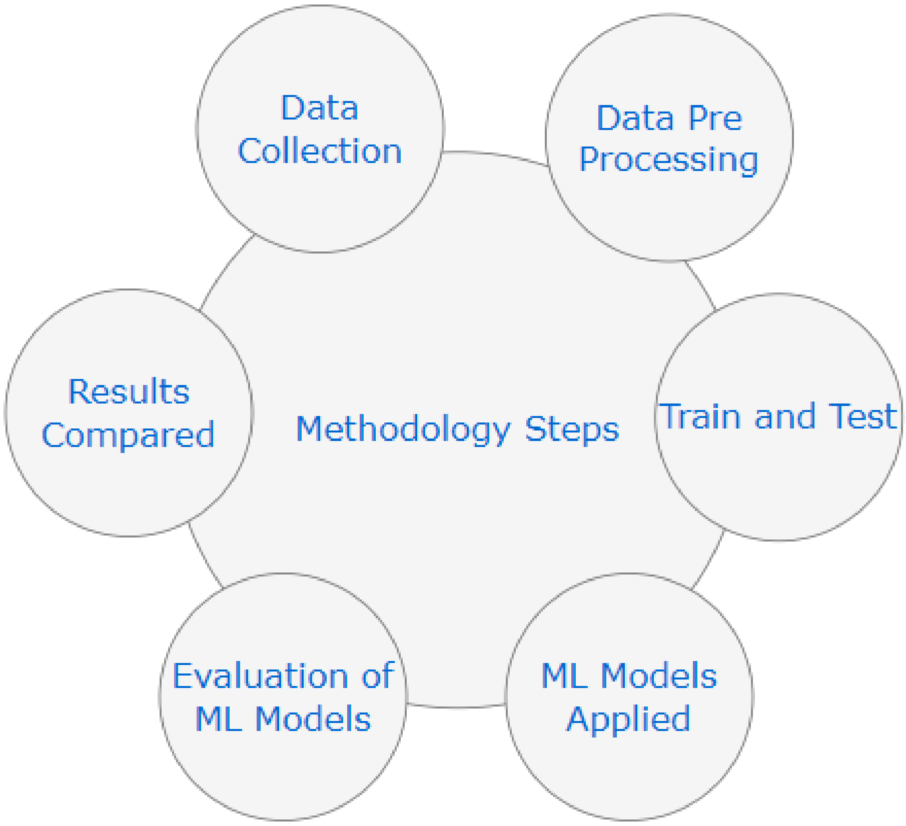

Figure 1: A flow chart showing the different steps involved in predicting the customer behaviour

3.1 Survey and Data Collection

The data for analysis was collected through an online survey which was made through google form. The research questionnaire consisted of 40 statements for perceived risks and 3 statements for consumer purchase intention. All statements were measured using a 5-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The questionnaire also gathered demographic information, such as age, gender, occupation, education level, and monthly income. Since the data was in terms of numbers from 1 to 5, it had to be pre-processed. Participants for this study were selected from PAN India who have shopped online at least once online, using snowball sampling method. A total of 308 consumers participated in the survey and their responses collected.

3.2 Data Cleaning and Pre-processing

During the preprocessing phase, unnecessary columns were identified and subsequently dropped to enhance model efficiency. Categorical variables were transformed to numeric variables using one-hot encoding, enabling machine learning algorithms to effectively process them. An average was computed for the statements, condensing risk assessment into a single numerical value for streamlined analysis. To define the target variable “purchase intention”, the Likert scale ratings was divided into three categories – Positive, Neutral and Negative. Ratings greater than 3 were categorized as positive, ratings less than 2 were categorized as negative and ratings which were either 2 or 3 were categorized as Neutral. Hence the problem was reduced to a classification problem where one predicts the customer purchase intention.

Additionally, to apply Machine Learning (ML) techniques, the dataset was divided into training and testing sets. Various machine learning models were applied to the training set, leveraging the preprocessed data for accurate risk assessment. This rigorous preprocessing laid the foundation for the development of effective predictive models.

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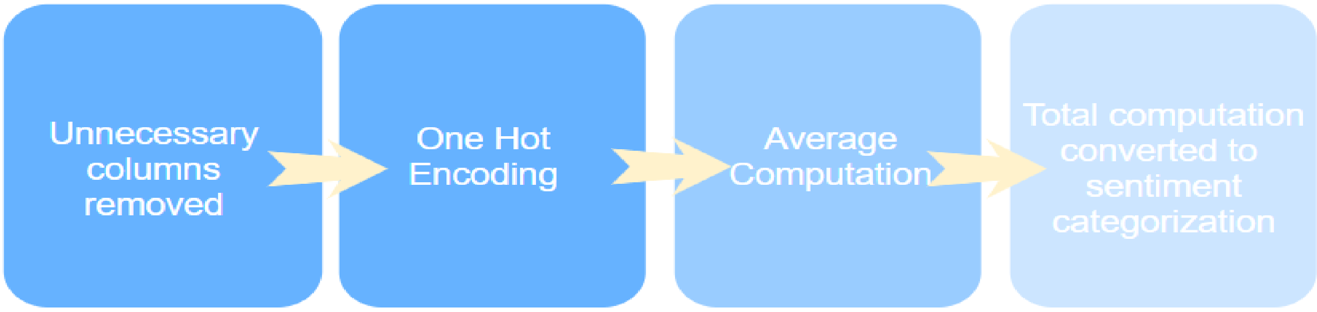

Figure 2: The pre-processing steps carried out before building the model

3.3 Prediction Techniques for Classification

3.3.1 Logistic Regression

Logistic Regression is a statistical model used for binary classification tasks. It estimates the probability of a given instance belonging to a particular class. It uses the logistic function to model the relationship between the dependent binary variable and one or more independent variables.

3.3.2 Decision Tree

A Decision Tree is a tree-like model that makes decisions based on features. It recursively splits the data into branches, where each node represents a feature and each leaf node represents a class label. It's a versatile algorithm that can handle both categorical and numerical data.

3.3.3 Random Forest

Random Forest is an ensemble method that creates multiple decision trees and combines their predictions. It helps to improve accuracy and reduce overfitting by aggregating the output of multiple weaker models. Each tree is trained on a random subset of the data with replacement.

3.3.4 Gradient Booster

Gradient Boosting is also an ensemble technique that builds multiple weak learners sequentially. Each learner corrects the errors of the previous ones. It is an effective algorithm for reducing bias and variance, leading to robust predictive models.

3.3.5 XG Boost

XGBoost is an optimized and highly efficient implementation of gradient boosting. It is known for its speed and accuracy in predictive modeling tasks. It incorporates additional features like regularization and parallel processing, making it a popular choice for competitions and real-world applications.

3.3.6 Ada Boost

AdaBoost is a boosting algorithm that focuses on misclassified data points. It assigns higher weights to them in successive iterations, allowing the model to pay more attention to the instances it struggles with. It combines the output of multiple weak classifiers to form a strong one.

3.3.7 Cat Boost

CatBoost is a gradient boosting library that handles categorical variables seamlessly. It is designed to work well with datasets containing a mix of categorical and numerical features. CatBoost applies a novel method to process categorical variables, improving prediction accuracy.

3.3.8 Naïve Bayes

Naive Bayes is a probabilistic model based on Bayes' theorem. It is commonly used for text classification and other tasks involving categorical data. Despite its simplicity, it often performs well and is computationally efficient.

3.3.9 Support Vector Machine (SVM)

SVM is a powerful algorithm for both classification and regression tasks. It aims to find an optimal hyperplane that maximizes the margin between classes. SVM can handle linear and non-linear decision boundaries using kernel functions.

3.3.10 K- Nearest Neighbours (KNN)

KNN is a simple and intuitive algorithm that classifies instances based on the majority class of their k-nearest neighbors in feature space. It doesn't make any assumptions about the underlying data distribution and can be used for both classification and regression tasks.

These algorithms offer a diverse set of approaches to classification tasks, and their selection depends on factors such as the nature of the data, interpretability, and the specific requirements of the problem at hand in the field of machine learning.

3.4 Evaluation Metrics

The performance of each of the above-mentioned ML models are assessed using several metrics from confusion matrix such as precision, recall, accuracy, and F1-Score. Accuracy is a measure of the overall correctness of the model. It is one of the important classification evaluation criteria that could be calculated from using the equation given below.

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

where, TP stands for True Positive, which is the number of instances that are correctly predicted to be positive, TN stands for True Negative, which is the number of instances that are correctly predicted to be negative, FP stands for False Positive, which is the number of instances that are incorrectly predicted to be positive and FN stands for False Negative, which is the number of instances that are incorrectly predicted to be negative.

Precision also known as positive predictive value, focuses on the accuracy of the positive predictions made by the model. It is calculated as the ratio of true positives to the sum of true positives and false positives.

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

Recall measures the ability of the model to capture all the positive instances. It is calculated as the ratio of true positives to the sum of true positives and false negatives.

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

F1 Score is the harmonic mean of precision and recall. It provides a balance between precision and recall.

4. RESULTS AND DISCUSSION

4.1 Results

In this section, the results of research, which involved the application of various classifiers to our dataset, with a primary focus on evaluating their model accuracy. The classifiers employed encompassed a diverse set of machines learning algorithms, including decision trees, support vector machines, random forests, logistic regression , bagging and boosting. The findings elucidate the comparative efficacy of each classifier in accurately predicting outcomes within the context of our study. Table 1 shows the accuracy of the various ML algorithms used on the data.

The data was collected, pre-processed, and analyzed. Various machine learning algorithms were applied to the dataset and the accuracy score was collected. Before calculating the accuracy score, the dataset was checked and seen if it was a balanced one or not. That is, it was checked if there were equal number of customers who had no intention to purchase, neutral and those who intended to purchase. The dataset was not balanced and hence we calculated the Recall, Precision, and the F1-score as well. Table 2 gives the recall score of the different ML algorithms used.

Table 1: Accuracy score of the different ML Algorithms used

Model Name	Accuracy
Catboost	74.19

Random forest	74.19
Gradient	73.12
XGB	72.04
SVM	72.04
Logistic	69.89
Decision tree	68.82
KNN	67.74
Adaboost	58.06
Navie Bayes	44.09

Table 2: Recall score of the different ML Algorithms used

Model Name	**Recall**
Catboost	0.74
Random forest	0.73
Gradient	0.73
XGB	0.72
SVM	0.72
Logistic	0.7
Decision tree	0.69
KNN	0.68
Ada	0.58
Navie Bayes	0.44

From Table 1, it can be observed that the Catboost and Random Forest model gives the highest accuracy whereas from Table 2 Catboost model gives the highest recall. Hence, algorithm can be used to predict the customer purchase intention. Various experiments were conducted on the data to assess the model's performance, yielding accuracy results ranging from 65% to 75%. The findings demonstrate that the CatBoost Classifier and Random Forest outperforms the other classification methods. Following closely, Gradient Boost Classifier also demonstrated strong performance.

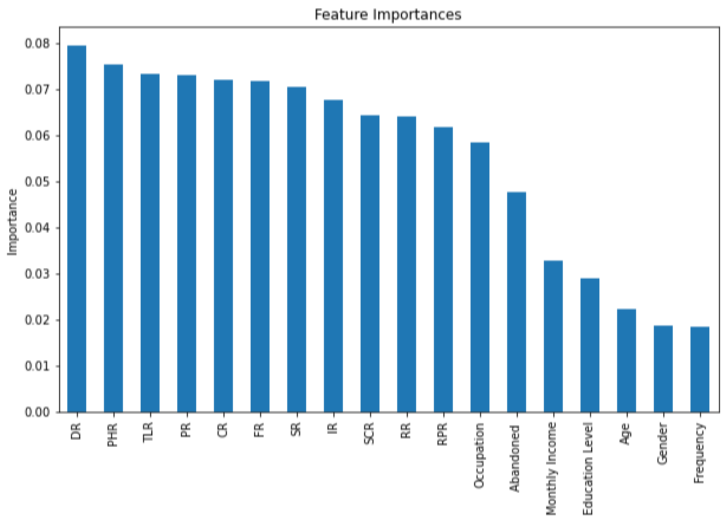

Figure 2: Bar chart showing the important features(risk) in deciding the purchase intention

The risks which are important in determining the customer purchase intention can be found using the Random Forest Algorithm. Figure 2 gives a bar chart showing the feature of importance in descending order. It was found that Delivery Risk is the major consideration as far as online purchase intention was concerned. This is true because customers perceive that the risk of delayed delivery or non-delivery directly affects their decision-making process regarding online purchases.

The second risk factor was Perceived Health Risk followed by Time Loss Risk and Cultural Risk. Considering the demographic factors of the participants in the questionnaire, it was found that occupation had the most significant influence on the customer purchase intention.

4.2 Discussion

Among all the ML Models, the boosting and bagging models worked best with the Likert scale data. Boosting and bagging models work well with Likert scale data because they are able to reduce the variance of the predictions. Likert scale data is often noisy and variable, which can make it difficult for machine learning models to learn accurate patterns in the data. Boosting and bagging models are able to reduce the variance of the predictions by averaging the predictions of multiple weak learners. Boosting and bagging models are also able to learn complex patterns in the data, which can be helpful for tasks such as predicting customer satisfaction or sentiment.

Our research aligned with previous research that revealed delivery risk has a negative relationship with online purchase intention. In the current era of fierce e-commerce competition, online retailers must closely monitor prompt delivery and customer service to meet consumer expectations. Any delays or lack of transparency in deliveries can result in customer discontent (Susilo et al., 2023). Customers perceive that the risk of delayed delivery or non-delivery directly affects their decision-making process regarding online purchases.

Perceived health risk also has a key influence in discouraging customers from buying online and is an important driver of online purchase intent. The risk of purchasing products online that may have adverse effects on my health influences customer’s decision to make online purchases. Customers worry about the accuracy and credibility of health-related information provided by online sellers. They are more likely to make an online purchase if the seller provides detailed information about the ingredients and potential side effects of health products.

Time loss risk is also a substantial deterrent to online purchasing and is an important driver of online purchase intent. Customers worry about spending time navigating complex website processes during online shopping. They are also concerned about the time and effort required to create and authenticate an account on store websites. They are concerned about wasting time on online shopping websites that may not have the products or services needed.

A customer's occupation can influence their perception of risk during online shopping due to factors such as income level, technical expertise, time constraints, occupational exposure to risks, industry-specific risk awareness, and personal risk tolerance. Understanding these influences can help online retailers tailor their strategies and risk mitigation measures to address the specific concerns of customers from different occupations.

This research offers practical insights for e-commerce platforms, marketers, and policymakers, enabling them to tailor strategies, enhance security measures and trust, and provide targeted interventions to mitigate perceived risks and optimize online purchase experiences.

5. CONCLUSION

As consumers navigate the digital marketplace, they are confronted with multifaceted risks, ranging from concerns about the safety of personal information to apprehensions regarding product quality, delivery reliability, and return policies. This prediction model will serve as a foundation for understanding how different risk perceptions influence online purchase intentions. This research will offer practical insights for e-commerce platforms, marketers, and policymakers, enabling them to tailor strategies, enhance security measures, and provide targeted interventions to mitigate perceived risks and optimize online purchase experiences. Consequently, drawing from the conclusions of this study, online retailers can implement various measures and these ML models to alleviate customers' perceived risks in the online realm. For instance, addressing customer concerns about delivery can be achieved by offering estimated delivery times, diverse options, and providing shipment tracking availability.

This study acknowledges several limitations. Firstly, this study focused on a select few factors, leaving room for researchers to explore alternative predictors in future studies on online shopping. Secondly, due to time constraints, the study did not include all the ML models. Future research could address this gap. Additionally, future studies could examine the mediating or moderating role of trust, consumers’ purchase intention, government influence, and cultural factors. Finally, a larger sample size could further benefit the overall model fit. Future research endeavors should aim to diversify samples by including participants from various developing and developed countries.

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