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An Improved Mathematical Model to Predict and Evaluate the Buying Assessment of Customers During a Pandemic Situation in Kerala

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Abstract

Nowadays, the knowledge-based economy has attracted more attention, especially online purchasing platforms where all activities and customer reviews are recorded. Implicit information from the records might be extracted using machine learning techniques. Industries and companies use the information to effectively comprehend consumer behaviour, possibilities, and threats. The coronavirus (COVID-19) outbreak has significantly impacted many facets of our daily lives, including shopping habits. Managers in the retail, distribution chain and public sector could benefit from determining customer behaviour regarding electronic devices. The research had seen online purchasing before the coronavirus epidemic, but its prevalence surged significantly during the illness. Due to COVID-19's high communication, The researchers must be aware of social isolation and personal well-being difficulties. These problems directly affect how consumers behave when shopping online. A Consumer Buying Assessment during Pandemic (CBAP) is proposed in this research. A proposed methodology is put out in this research using ml algorithms to forecast customer behaviour. Five individual classifications and combinations with bagging and enhancing are investigated on a dataset from an online retailer. According to the findings, the choice tree ensemble method with Bagging produced a model that was 95.3% accurate in predicting customer behaviour. Additionally, correlation analysis is carried out to identify the key elements affecting the number of online purchases made during the coronavirus epidemic.

Keywords: *pandemic, buying assessment, neural network, a mathematical model.*

1. Introduction

A severe respiratory condition known as coronavirus disease (COVID-19) was initially identified in Wuhan, China, in Dec 2019 [1]. Initial COVID-19 indications include dry cough, fever, and fatigue, typical of various respiratory illnesses. Physical symptoms, a throat infection, and a loss of flavour and smell would follow, and serious symptoms, including pneumonia, severe respiratory conditions, and even heart problems, would appear in the later stages of the illness. Numerous studies on COVID-19 have been published from various angles, including the transmission rate, drug and vaccine development, general health, and mental problems; nevertheless, consumption patterns have gotten less attention.

Thanks to the Internet, knowledge-based businesses, like online purchasing, have existed for a while. From logs of the online purchasing sites, implied knowledge might be

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extracted using machine learning techniques [2]. Industries and companies use the information better to comprehend consumer behaviour, possibilities, and dangers. However, online buying became more popular after the COVID-19 epidemic. Due to the disease's rapid transmission rate, The research must remain at home and practise societal and self-isolation. The study must give extra consideration to and offer special services for the elderly and persons with underlying illnesses, such as cancers, multiple sclerosis (MS), respiratory symptoms, heart issues, hypertension, and diabetes [3]. These factors have a significant impact on customers' shopping habits.

Today, significant initiatives like Siri from Apple, Eco from Amazon, Google, Facebook, and Microsoft use machine learning algorithms to monitor customers' shopping habits automatically and deliver personalized services [4]. However, applying machine learning techniques is just for large-scale research initiatives. These techniques can help small and medium-sized businesses (SMEs) increase productivity. Other significant factors, such as the spread of COVID-19, might be used to demonstrate the suitability of machine learning approaches for SMEs [5]. In light of challenges with urban traffic control, internet advertising and shopping are becoming more widespread [6]. Online catalogues assist in cost and quality comparisons [7].

Additionally, the time needed to purchase a product might be significantly decreased. In any e-commerce application, it's crucial to understand user behaviour and deliver good service quickly [8]. Users may attempt to purchase a product but cannot add it to their shopping basket or encounter payment issues. As a result, customers abandon the website without making a purchase. For many online sellers, this is a crucial problem [9].

Understanding customer behaviour is essential for developing practical e-commerce applications, but it can be challenging to pinpoint the motivating elements that lead people to make purchases online [10]. Techniques for machine learning look for customer behavioural patterns using data analytics technologies [11].

The fundamental problems in e-commerce were always raising consumer pleasure with internet purchases and increasing the precision of consumer need forecast. Segmentation, clustering, association rules, and based classification techniques are a few examples of machine learning and data approaches successfully used in prior studies to anticipate significant aspects of e-commerce [12]. Issues with COVID-19 highlighted how crucial it is to focus on customer pleasure while shopping online. As a result, a model using machine learning methods is presented to forecast consumer information in social buying. The contributions of the suggested way can be summed up as follows:

- A prediction model is used to forecast consumer behaviour in an e-commerce context during the COVID-19 era in Kerala.
- Bagging and enhancing the classifier makes it possible to forecast customer behaviours for online purchasing accurately.

The remainder of the paper is listed as follows: section 2 indicates the background to the consumer buying pattern analysis during a pandemic. The proposed Consumer Buying Assessment during Pandemic (CBAP) is used to analyze the buying pattern of the consumers in Kerala. The software analysis and performance outcomes of the proposed system are enumerated in section 4. The conclusion and future scope of the system are shown in section 5.

2. Background to the consumer analysis during a pandemic

Several previously published research findings on consumer behaviour are examined in this section. Nicola et al. carried out a comprehensive analysis of the socioeconomic effects of COVID-19 on the global economy, such as familial relationships, domestic abuse, and home electronic games, as well as the following industries: agriculture, crude oil and oil, production, property investment and housing, schooling, economic, and pharmacological [13]. COVID-19 has had an impact on people's lives in a variety of ways, particularly on their buying habits. Increasing consumer need for necessities like food, shopping, and medical services gave retailers and network operators new opportunities to provide customers at home.

According to research by Wang et al. [14], customers' behaviour regarding food stockpiling can be understood. They demonstrated that during COVID-19, the size of the food stockpile was approximately doubled. Additionally, they concluded that women with higher income and educational levels are more likely to purchase more food, remarkably fresh food. Conversely, the demand for non-essential items like clothing, footwear, and household appliances has decreased, which has resulted in a decline in sales for shops in 2019. As a result, models are required to forecast customer behaviour so businesses may make the necessary preparations to survive in this market.

Pantano et al. [15] provide two models to forecast GDP increase in Japan: random forests and gradient enhancing. The gradient enhancing model outperformed the decision tree model in comparing the two models. He asserts that macroeconomic forecast methodologies are encouraged by machine learning algorithms. Yoon et al. studied [16], and the relationship between COVID-19's macroeconomic effect and the impacted economies is depicted. The AD-AS model, which considers critical requirements for deciding policies to handle such financial turmoil, is introduced. They conclude that every action should be done before an economic downturn happens because it'd be too long if The research waited until COVID-19 was over before considering its issues and potential remedies.

Barua et al. showed the model [17], formal modelling is used to examine the validity of the Knowledge Creation Procedure (KCP) in networking and social organizations. The study of human engagement in online interactions and discussion of the applicability of the suggested user interaction management strategy.

Souri et al. showed the default risk of people about their attributes is calculated using a dataset from the Turkish statistics community [18]. 22,745 observations with 14 characteristics make up the dataset. The j48 classifier, the Bayesian networking, the Naive Bayesian, the neural network, the regression models, and the randomized forest were studied. Their outcomes were contrasted based on the accuracy, efficiency, ROC curve, and average square error. The best classification system for risk identification is finally chosen. Consumer preferences for particular products appear to substantially impact the decision-making process for e-commerce software, according to experiments conducted on an actual database [19].

A paradigm was put forth by Souri et al. to forecast consumer behaviour in an e-commerce setting [20]. The framework, often known as the "customer modelling process," consists of two steps. Product connections are investigated to forecast customer incentives, explicitly creating a prospective item set. The contenders are finally chosen based on consumer preferences for the product's attributes. When an item is supplied to a consumer behaviour system, the programme can return goods that the customer is likely to buy shortly. The findings of a different study by Cirqueira et al. outlined the use of computer learning techniques to analyze the Instagram user behaviour of a fashion brand [21]. The cross-industry standard extraction procedure employs clustering techniques and associated rules. They concluded that relevant information might be engaged in marketing plans when extracted utilizing the suggested detailed model.

Sahoo et al. provide a supply chain forecasting model based on simulated data [22]. He identified certain traits that makeup pandemic coronavirus to identify a specific distribution network diversion risk. He demonstrated how simulation findings might be used to examine and foresee how the sickness will affect the profitability of the distribution chain. AnyLogistix modelling and optimization tools are used. Impacts of

COVID-19 on distribution chain and managerial insights are taken into account, both short-term and long-term.

Ivanov concluded from the simulated findings that the timing of service shutdown and opening at various levels might be a crucial determinant of COVID-19's impact on supplier performance. Ivanov et al. suggested a brand-new two ensembles model for machine learning [23]. Support vector analysis and an adaptive neuro-fuzzy inference system were combined. Their investigations reveal that the suggested model outperforms single and two-phase models studied and contrasted with their method in terms of model performance [24]. Predicting customer behaviour could be extremely helpful for merchants and distribution network sector managers, as inferred from the study studies described above. Consumer behaviour is crucial in deciding the potential success of e-commerce apps.

3. Proposed Consumer Buying Assessment during Pandemic

The sustainability of a long-term sale strongly relies on customer behaviour and wants. Particularly in light of the COVID-19 epidemic, consumer behaviour is evolving daily. Predicting buyer behaviour may therefore be essential for future corporate strategy. An e-commerce business that can predict consumer behaviour can benefit in several ways, including higher customer buy rates, higher revenues and customer happiness, and more competition. This study uses deep learning and statistical methodologies to anticipate customer behaviour. The correlation among multiple components is computed and examined statistically. A prediction model is suggested as part of the method of machine learning to forecast consumer behaviour in online buying.

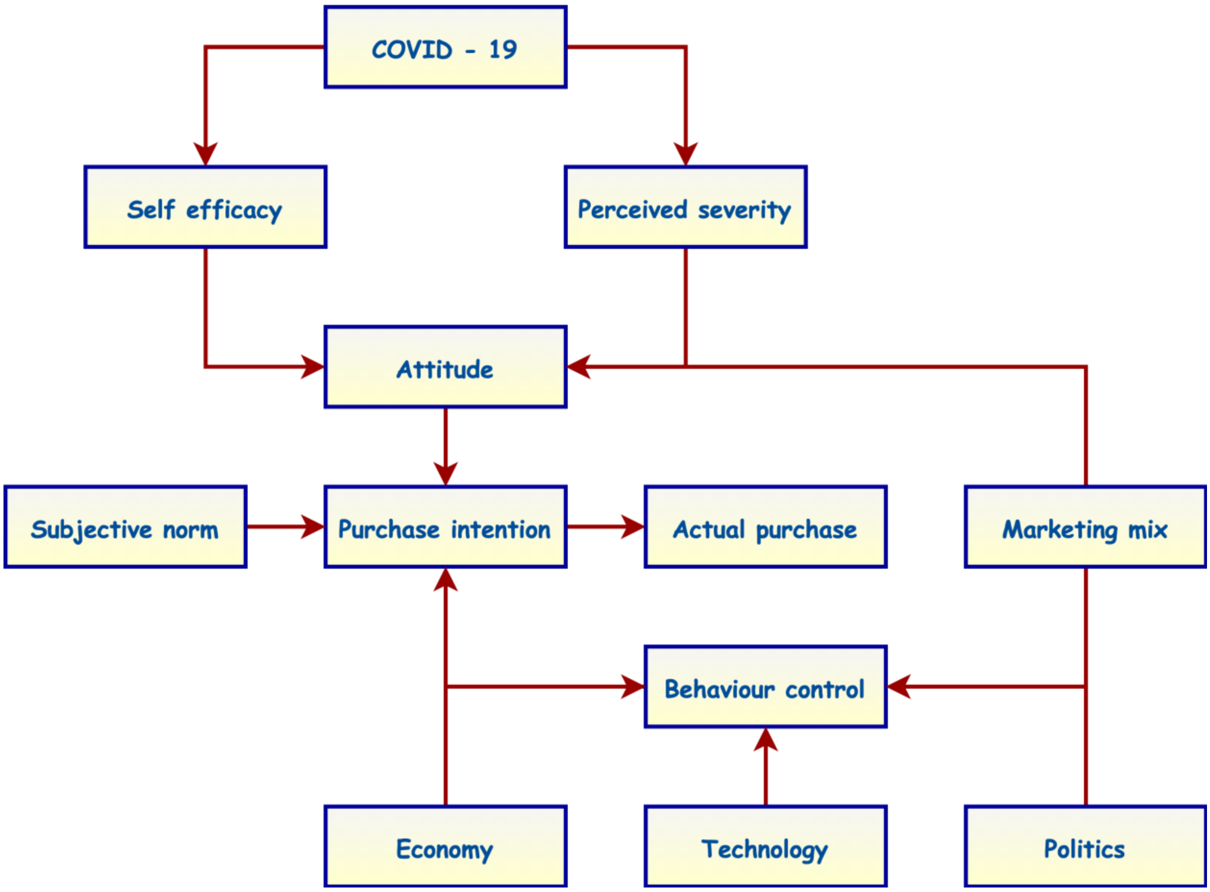

Fig. 1. The consumer buying pattern analysis of the CBAP

The consumer buying pattern analysis of the CBAP is shown in Fig. 1. The pandemic and the buying patterns are interrelated. The self-efficacy and the perceived severity are linked to finding the attitude. The purchase intention, actual purchase, marketing analysis, behaviour control, economy and politics are analyzed to test the consumer buying pattern in Kerala. Various methodologies are investigated to forecast consumer behaviour based on information gathered from online purchases made at the DigiKala website (www.digikala.com). Digi- Kala is one of Mideast's most popular and prosperous internet retailers. The optimal technique with the maximum accuracy is determined by comparing the well-known supervised machine learning algorithms.

First, data screening is discussed in the remaining paragraphs of this chapter. Then a basic explanation of the correlation test. The suggested machine learning approach for forecasting customer behaviour is then described. The assessment methods used to rate the proposed method are presented at the section's conclusion.

3.1 Preprocessing

To speed up implementation and enhance the outcomes, preprocessing the data must be done first. It standardized the dataset so that the variables are normalized using Equation (1):

$$n_V = \frac{O_V - Old_{min}(n_{max} - n_{min}) + n_{min}}{Old_{max} - old_{min}} \tag{1}$$

The old vector is denoted O_VThe minimum and maximum vector values are denoted Old_{min} and Old_{max}. The normalized sample is denoted n_{min}. This study's target range for normalization is [0, 1]. The normalized vector is denoted in Equation (2).

$$n_V = \frac{O_V - old_{min}}{old_{max} - old_{min}} \tag{2}$$

3.2 Correlation analysis

The influence of COVID-19 on customer purchase quantity in Kerala is the "Effective" characteristic, which is the eleventh in this article's construction of the information. After normalizing the data, it computed the correlation between the traits to identify the one that correlates most strongly with the "Effective" characteristic. Equation (3) is employed to calculate the Pearson connection.

$$P_{i,j} = C(i,j) = \frac{cov(i,j)}{p_i p_j} = \frac{E([i - b_i][j - b_y])}{p_i p_j} \tag{3}$$

where $P_{i,j}$ is the Pearson relationship among the two variables, i and j, whose correlations The research is involved in calculating. Standard deviations for i and j are p_i and p_j are, respectively, while anticipated values for i and j are b_i and b_j. For the Correlation coefficient to be accurate, the standard deviation must be high and finite. cov stands for covariance operator, E for expected utility operation, and C for the coefficient of correlation. The values "yes" and "no" are accepted by the "Effective" feature. The answer "yes" implies that COVID-19 impacted customers' purchasing decisions, whereas the answer "no" shows that COVID-19 had no impact.

3.3 Classification

Both descriptive and simulation methods are typically designed using classification techniques. With the classifiers above, ensembles meta-algorithms, enhancing, and bagged are investigated to increase the precision of the suggested approach. The ensemble approaches combine several classification techniques to outperform each categorization algorithm individually.

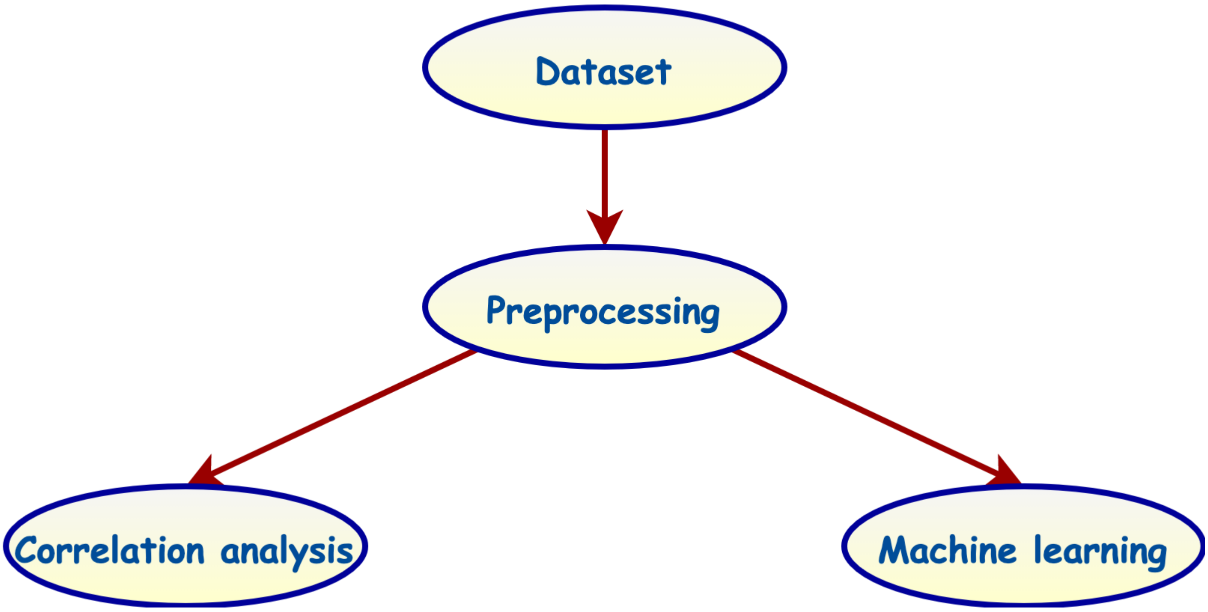

Fig. 2. Classification model

The classification model of the CBAP is represented in Fig. 2. The preprocessed data is analyzed by correlation function and machine learning model. By lowering bias and variance, enhancing and bag are ensembles approaches that turn weak classifiers into strong classifications. A statistic approximations approach called Bagging employs many small selections of your information to calculate a statistical measure, such as a mean. It is a valuable technique when there is less data and The researcher want a closer estimate of a statistical metric. Boosting employs a weighted sum but functions similarly to Bagging. In the training phase, they create N learning data using random sampling and replacing samples from the entire dataset.

The samples in enhancement are weighted, and some examples have a greater likelihood of influencing the classification outcomes. But in Bagging, every model gets an equal opportunity to participate in the learning procedure. Bagging improves the precision of the weak classifications by concurrently training the learners. In contrast, Boosting introduces invalid types, with every classifier attempting to outperform the one before and bagging and enhancing predictive performance by lowering the bias and variability of a classification algorithm. This research studies individual classifications and their combinations with Bagging and enhancing to predict customer behaviour.

3.4 Materials and methods

A new frontier is different from the one. The research was familiar before the COVID-19 epidemic emerged, one that is more complicated in Kerala. Consumer views and actions have changed significantly. New behaviours and behavioural patterns are anticipated to stick around despite the disaster. The survey's objective was to discover these shifts in consumer behaviour. It was carried out using a structured questionnaire primarily dispersed electronically between January and February 2021 via media platforms. Online Surveys were employed to compose the survey questions, which Twitter and Instagram scattered; a particular age range was personally addressed—the group over 62.

Respondents were chosen randomly to guarantee a true reflection of the consumer segment. A minimal sample of 385 participants was computed using the inverse linear root technique, a significance level of 0.15, a reliability level of 0.75, and these parameters. Four hundred twenty customers participated in the study, which can be considered a sufficient number of participants to generalize the research findings. These demographic characteristics were examined in further detail in light of the nation's altered economic condition due to the COVID-19 epidemic. These analytical steps were used to conduct the analysis:

1. Establishing contingency charts to identify shifts in consumer behaviour based on various demographic characteristics

2. To identify any correlations between appropriate measures of consumer behaviour and participants' demographic characteristics (age, gender, salary, and employment industry), Fisher's considered test and Pearson's chi-square exam were conducted at a significant level of 5%. The dependency coefficient (Cramer's V) was computed, and its importance was examined, assuming mutual reliance was established. The following hypothesis was established considering the earlier findings listed in the existing literature:

Hypothesis 1 (H1). The key issues consumers face because of the COVID-19 epidemic (buy re-evaluation, alterations in financial status, changes in house brand preferences, purchasing patterns) are statistically correlated with the demographic characteristics of the participants in Kerala.

Hypothesis 2 (H2). Both the persistence of new buying habits in the post-pandemic era and the generational aspects have a reciprocal relationship with the financial status of customers (greatly exacerbated, better, or no changes in situation) in Kerala.

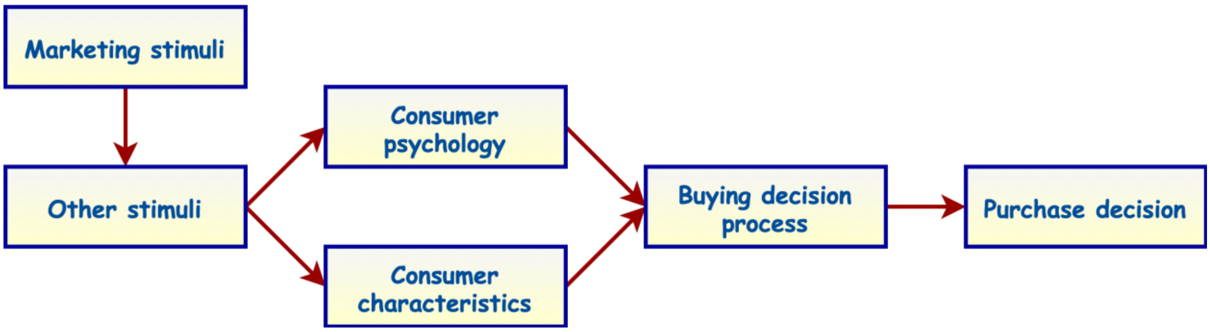

Fig. 3. The consumer buying pattern prediction model

The consumer buying pattern prediction model is shown in Fig. 3. The simulation of the marketing and other patterns is given as input, and the consumer psychology and characteristics are fetched from the dataset. The consumer buying decision and decision purchase are predicted using machine learning. The relationship among groups of measured variables organized in graphs and tables is ascertained using correspondence research. This analysis aims to evaluate the interrelationships between factors and delineate the composition of the under-investigation dependence.

A two-dimensional dependency table with the corresponding absolute frequency (n_{xy}) serves as the analyses' input matrix. The frequency of appearance of the parameter X, which has values $i_x, x = 1,2,\cdots, N$, and the factor j, which has values $j_y y = 1,2,\cdots, N$, is listed in each field of the chart. The following equations are used to get the row marginal relative frequency n_{x+} of the parameter i and the column marginally absolute frequency (n_{+y}) of the parameter y is shown in Equation (4).

$$n_{x+} = \frac{\prod_{y=0}^{N} n_{xy}}{n_{+y}} \text{ and } n_{+y} = \prod_{x=0}^{N} n_{xy} \tag{4}$$

The marginal frequency is denoted n_{x+}, and n_{+y}. The normalized two-dimensional vector function is denoted n_{xy}. A correlation matrix P is then constructed using the computed row and column margin frequency. Its constituent parts are relative frequency p_{xy}And it is shown in Equation (5).

$$p_{xy} = \frac{n_{xy}}{\sum_{i=0}^{N} n(i)} \tag{5}$$

The normalized two-dimensional vector is denoted n_{xy}And the number of samples is denoted n(i). Their profiles are established to guarantee the compatibility of row and column groupings. In the instance of the x-th subcategory of the row factor, the row profiling $p_{y/x}$ are conditional relative frequency indicating the architecture of the column parameter. In the instance of the y-th category of the columns data, the column features $p_{x/y}$ Are conditional relative probabilities indicating the architecture of the row parameter. The conditional probability is denoted in Equation (6).

$$p_{y/x} = \frac{n_{xy}}{n_{x+}} = \frac{p_{xy}}{p_{x+}} \text{ and } p_{x/y} = \frac{n_{xy}}{n_{+y}} = \frac{p_{xy}}{p_{+y}} \quad (6)$$

The normalized vector is denoted n_{xy}The conditional probability is denoted p_{xy}. The marginal vector and marginal probability are denoted n_{x+}, n_{+y} and p_{x+}, p_{+y} . Variable dependency is reflected via changes to the row and column characteristics. The coordinates of locations in the multidimensional feature environment, where the chi-square euclidean distance is used, are determined using the unique row and column characteristics. The categories are more comparable, and their interdependence is more significant the nearer the points are to one another on the connection map. The values in the connection map determine the variance of the multifunctional points. Total inertia is used to calculate the variability of multivariate issues and is expressed in Equation (7).

$$X^2 = \prod_{x=0}^{N} p_{+y}\left(d_y\right)^2 \quad (7)$$

where d_y is the chi-square separation across the characteristic of the column y, p_{+y} is the conditional margin probability of the column y, and X is the overall inertia. Similarly, the same process is used to establish row groups.

3. Comparative examination of additional pertinent data from the survey of participants from Slovakia that are reviewed and examined in light of other research and surveys published internationally.

3.5 Questionnaire development

Two sections make up most of the survey. Participants' biographical information was gathered in the first segment, including their age, gender, economic status, degree of education, profession, employment status, and several online purchases during the COVID-19 epidemic. It invited the participants to choose the product lines from which they had made online purchases in this area. It determined these market segments based on a well-known online marketplace in Kerala.

Participants were asked about their plans to make online purchases during the epidemic in the second phase. In the setting of the online purchases, George looked at the effects of behavioural attitude, normative beliefs, and perceived behavioural control. It modified George's study's behavioural attitudes, normative beliefs, and scented behaviour control items because the contexts were similar. It used three variables for each of these concepts to measure them. It used three measures to assess behavioural intention and two items to evaluate actual behaviour.

Six items were developed to gauge pandemic worry within the study's overall context. The research created a multi-item Likert scale for every item with a five-point (1: Extremely Disagree to 5: Strongly Agree). The survey was completed in Kerala. Before the dissemination, two PhD candidates reviewed the questions' language and grammar. Before the survey was distributed, it revised the document based on their suggestions. Cronbach's alpha was used to measure item reliability, and composites item reliability was used to evaluate internal uniformity among questions. The research assessed loadings and mean volatility to determine the validity and composite reliability.

The research assessed discriminating validity to check that the survey questions that were meant to be linked were indeed unrelated. In addition to validity and accuracy evaluations, the study test determines whether there was multicollinearity between the variables. The variance inflation coefficients determined for every construct related to the other constructs were used in this test.

3.6 How covid-19 shaped the future of online shopping

The coronavirus epidemic, which has significantly influenced e-commerce and internet sales, can be seen as a pivotal moment that will encourage more individuals to shop Internet in the next. People were encouraged to shop online through COVID-19. Before the epidemic, a few online customers had never done online shopping. Following isolation, people unavoidably had to use online purchasing to meet some of their demands. Even after the epidemic, specialists predict that the research will behave differently and change in every area of life. Therefore, it is envisaged that various items used in daily life will be supplied rapidly and bought through internet retail rather than physically procuring from shopping.

In this regard, businesses and online retail outlets encountered issues during the delivery and inventory epidemic. Many companies have considered it a duty and need to address their weaknesses in the digital domain, users brought on by the epidemic. More transactions will be made online in place of physical shops, and customers will have easier access to these businesses. Companies will simultaneously develop new models and emphasize social media marketing to offer clients quicker and higher-quality service. Since the coronavirus, there has been a rapid shift in trade and revenues from physical establishments to online ones, and this trend will only continue. Almost all age groups aim to work in this region, regardless of age. The pandemic-induced conditions gave internet purchases, which had been growing before the epidemic, a significant boost, and individuals are now more interested in online buying globally.

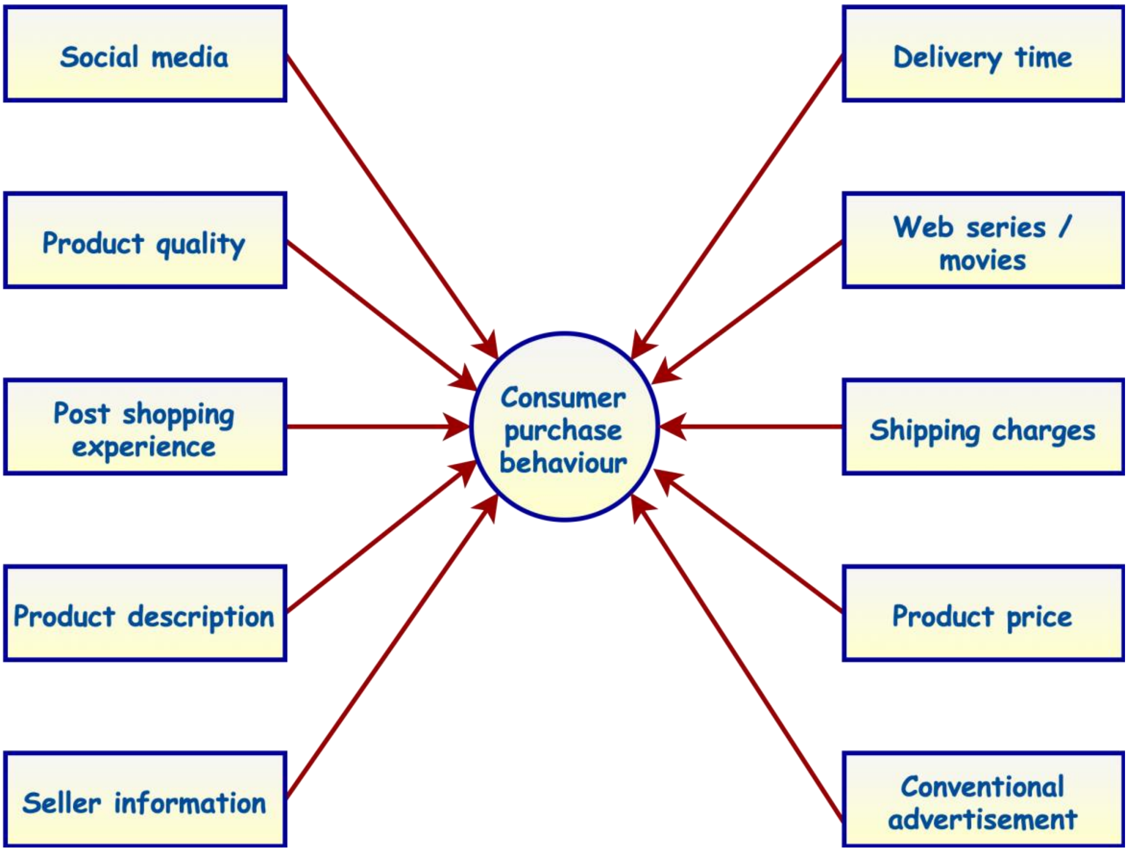

Fig. 4. The consumer purchase behaviour affecting factors

The consumer purchase behaviour affecting factors is shown in Fig. 4. The different aspects include social media, product quality, post-shopping experience, product description, seller information, delivery time, web series/ movies, shipping charges, product price, and conventional advertisement. COVID-19 served as a wake-up call for nations worldwide to establish the technology infrastructure necessary to distribute goods and services to customers via online networks to be self-sufficient. E-commerce and internet sales are undoubtedly the initial and most practical approach that springs to mind when thinking about selling things to other nations. The primary takeaway from the epidemic for companies and authorities is that e-commerce and internet orders will transform global trade in the decades to come and that digital shopping will take an active and crucial part in the selling and marketing of virtually every merchandise and product category.

4. Experimental analysis and outcomes

The Amazon Sales Dataset exhibits the online buying pattern of people in Kerala by shortlisting the state as Kerala and the period from 2020 to 2022 [26]. The dataset's records are each comprised of product ID, name, category, discounted price, actual price, discount percentage, rating, rating count, about product, user ID, use name, review ID, image link, and product link. The demographic characteristics are race, age, schooling, and occupation. The following four features discuss potential consumer illnesses. The final two segments differ in the number of purchases made in two months COVID-19 epidemic (up to and following March 20, 2020) in Kerala. This experiment employed a PC with an Intel(R) Core(TM) i74700 HQ CPU running at 2.40 GHz. RAM is 8.0 GB. The seaborn library version 0.10.0 and Python anaconda version 2020.20 are used for correlation tests, and Weka version 3.8.1 is used to build and test machine learning algorithms. Python and R are both available for free and public sources used in Anaconda. It is frequently employed for computer research using machine learning methods.

Table 1. Experimental data

Parameters		Response (count)	Response (%)
Gender	Men	50	25
	Women	150	75
Education	High school	50	25
	Bachelor	70	35
	Master	40	20
	PhD	40	20
Average cart price	Less than 1k $	25	12.5
	1k to 5k $	80	40
	5k to 10k $	55	27.5
	Above 10k $	40	20
Prepayment	Yes	120	60
	No	50	25
	Maybe	30	15

The experimental data used for the analysis is shown in Table 1. Fifty men and 150 women were considered for the research, with different education levels varying from high school, bachelor's, master's, and PhD. The average cart price of the purchase is measured and changed from 1k $ to above 10k $. The payment mode is monitored, whether prepayment or cash on delivery. The data is collected from the participants from Kerala, and the response percentage is computed and plotted.

Fig. 5(a). Satisfaction level analysis

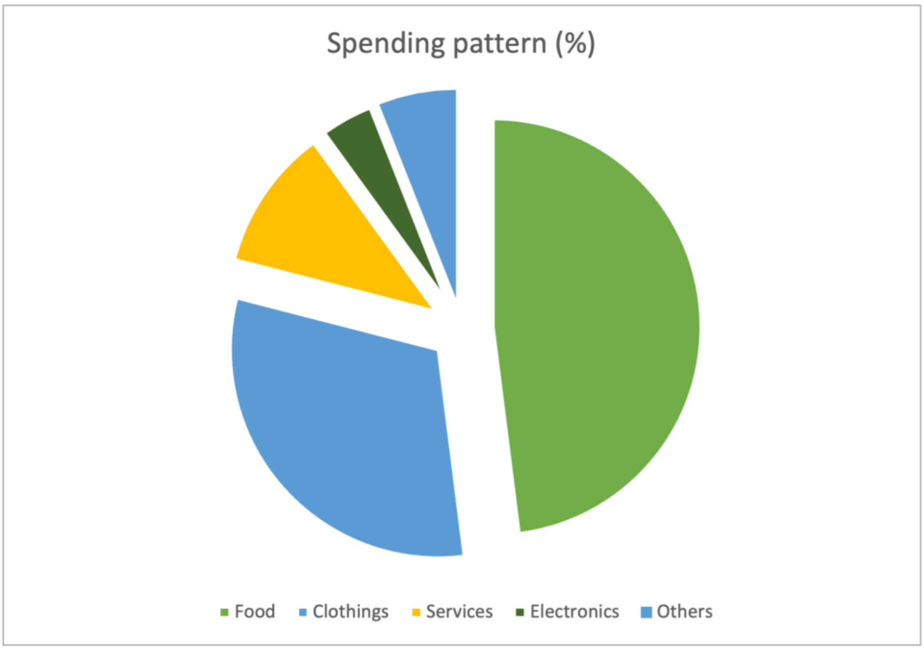

Fig. 5(b). Spending pattern of the consumer analysis

The consumer analysis's satisfaction level and spending pattern in Kerala are measured and plotted in Fig. 5(a) and Fig. 5(b). The consumer purchase in Kerala is analyzed based on items like food, clothing, services, electronics, and others. The satisfaction level of the consumers in Kerala is analyzed based on feedback like low-quality products, high prices, payment methods and counterfeit products. The results show the higher experimental outcomes of the CBAP with the machine learning model.

Table 2. Experimental outcome analysis

Variable	Product	Mean (%)	Standard deviation (%)
Behaviour control	1	3.73	1.02
	2	3.97	1.53
	3	4.63	2.04
Purchase intention	1	3.65	1.05
	2	3.85	1.42
	3	4.52	2.41

The experimental outcome analysis of the CBAP is measured and tabulated in Table 2. The Kerala participants' consumer behaviour control and purchase intention are monitored, and the results of different products, such as the mean and standard deviation of the consumer experience, are measured and tabulated. The proposed CBAP with a machine learning model enhances consumer purchase behaviour and predicts with higher accuracy. The proposed CBAP with higher prediction results shows the lower mean and lower standard deviation results.

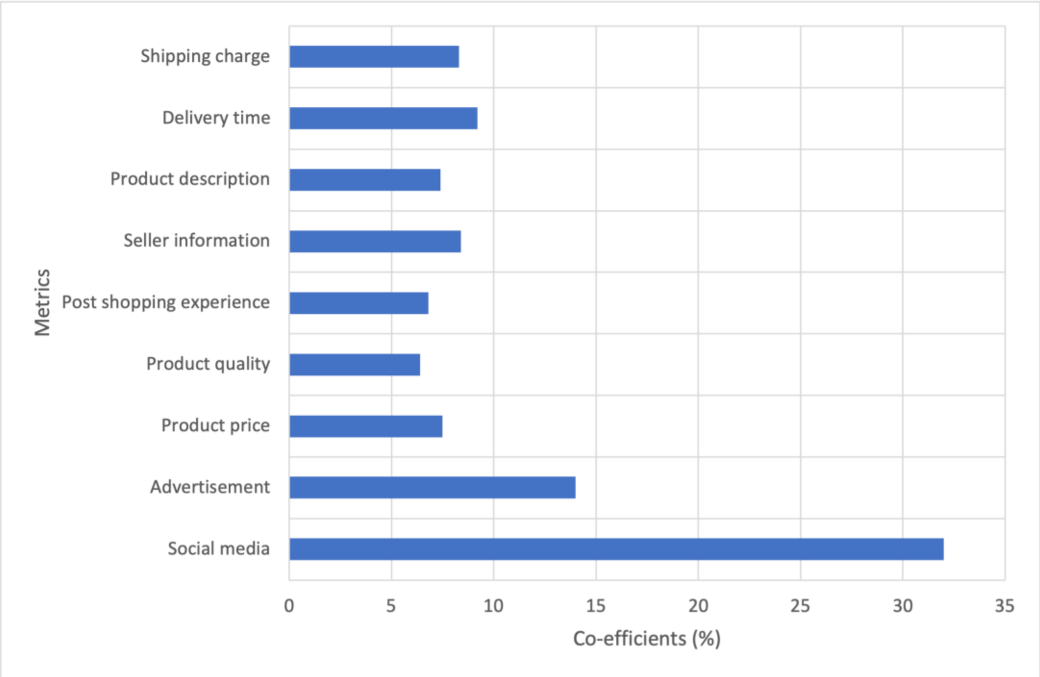

Fig. 6(a). Consumer buying pattern coefficients analysis

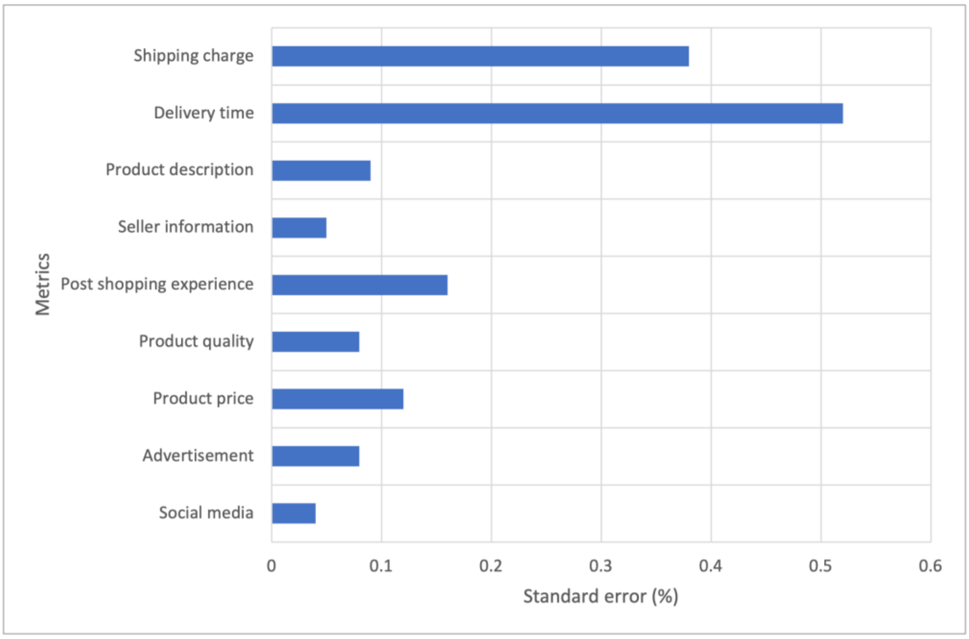

Fig. 6(b). Consumer buying pattern's standard error analysis

The consumer buying pattern's coefficients and standard error are measured and plotted in Fig. 6(a) and Fig. 6(b), respectively. The different metrics about the consumer purchase affecting factors such as social media, product quality, post-shopping experience, product description, seller information, delivery time, web series/ movies, shipping charges, product price, and conventional advertisement are considered for the experimental analysis. The proposed CBAP framework with a machine learning model predicts the consumer purchase pattern with lesser error.

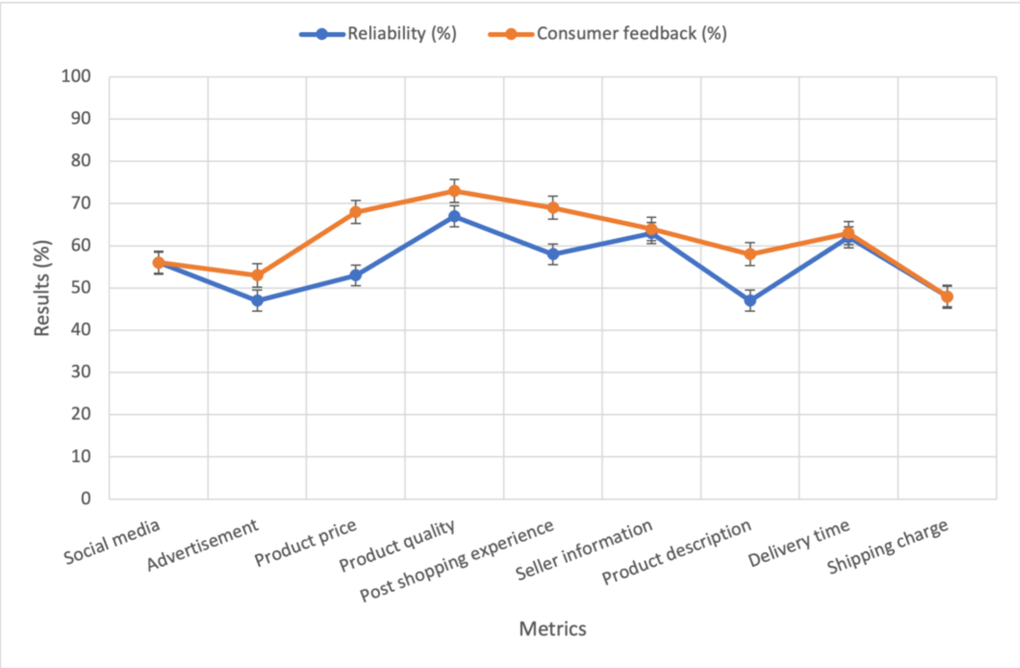

Fig. 7. Experimental result analysis

The experimental result analysis of the proposed CBAP framework is shown in Fig. 7. The different factors affecting the consumer buying pattern in Kerala are analyzed, and the results are compared to explore the highest impacting factor. The proposed CBAP framework with a machine learning model enhances the prediction accuracy with higher consumer feedback about the products or services. The results show the higher impacts of factors influencing the consumer buying factors in Kerala.

The proposed CBAP framework with a machine learning model is analyzed, and the results are plotted in this section. The experimental results show the higher efficiency of the proposed method with higher consumer buying pattern analysis efficiency.

5. Conclusion and future study

This work studies the effect of COVID-19 on customer behaviour in Kerala. A proposed methodology predicts consumer behaviour in online buying during the COVID-19 epidemic. It examines five categorization models, and logistic regression generated the most accurate result with a 94.6% accuracy rate. Then, Method and Boosting aggregate meta-algorithms are applied to increase the classifiers' accuracy. Similarly, decision trees produced the most outstanding results. DT groups with Bagging outperformed other base classification ensembles with bags and boosting, achieving better outcomes of 95.3% accuracy.

Additionally, Pearson correlation determines the factors influencing forecasting customer behaviour. The characteristics that have the most significant influence on consumers' online purchase behaviour are discovered to be age and illness. Meta-heuristic methods could be investigated in future studies to improve the accuracy of predicting consumer behaviour. For increased accuracy, other classifications could be applied to the prediction. A dataset containing more COVID-19 pandemic-related properties could be used to build a predictive model. The proposed framework is limited by the study done in Kerala and limited resources collected from the participants. The outcomes of the framework can be increased by using the big data analytics model and including the social network analysis framework.

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