

# College Students Consumption Behavior Under the Background of E-Commerce and Smart Logistics Technologies

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## ABSTRACT

The impact of online systems and processes worldwide makes online purchasing popular. College students are among the possible buyers of E-commerce. This study looks at the characteristics that influence college students' online purchase intention in one of Chinese quickest cities. With smart logistics, it is possible to follow the transportation and dispatch of goods and services in almost real-time. Smart logistics has long been implemented by e-commerce enterprises, taxi apps, and food delivery services. The student's Consumption Behavior Approach (SCBA) is suggested in this article. The survey collection is analyzed to group the learner's research on online activity and smart logistics technology. Because the sample group is thus tiny, approaches are used. The findings reveal that fun, risk, and cultural pressure substantially influence pupils' online buying behavior. SCBA grouping produces three behavioral sections: that mostly impacted by social power and perception of risk, that features by pleasure and online trust.

## KEYWORDS

college students, consumer behavior, E-commerce, smart logistics technology, online shopping

## INTRODUCTION TO CONSUMPTION BEHAVIOR

In Western nations, limited e-commerce in Arab nations is not well understood. As a result, the study provides a fresh perspective on it. The issue leads to additional discussion and study, particularly on what could be done to increase the popularity of e-commerce in Arab nations (Nayyar et al., 2020). As a result, the work might be classified as an introduction. There is a significant surge in the use of Web store and Online. However, the once-famous 'dot com era' is gradually fading. Ecommerce is the buying and selling of data, goods, and activities through networked computers (Zhao et al., 2021); due to this classification, internet shopping is classified as e-commerce.

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Enhancement, a specialty concentrate, expansion, preserving versatility and segmentation are among the key success factors for e-commerce that have been recognized. Other key performance indicators include using the proper equipment to handle a crucial perspective, excellent service, and effective interconnection. E-commerce has grown due to factors such as growing cellphone use, affordable and convenient internet connection, and the heavy workload of ordinary workers.

Goods must be transported and stored efficiently from their source to their final destination, and this process is called logistics. Smart logistics technology is utilized to fulfill this goal of meeting client needs quickly and affordably. Online buying has been steadily increasing. In 2009, internet shopping was expected to be worth \$237 billion in the United States alone (Gunasekaran et al., 2018). Likewise, Nielsen claimed that practically all Web users in emerging nations like Korea and China planned to purchase online. Arab nations have less spectacular e-commerce growth compared to their emerging rivals. Over half of Netizens in Arab nations have never done online buying, making them the weakest adopters of internet purchases (Amudha et al., 2018).

The Jordanian Department of Commerce stated that the growth of e-commerce is still very much in adolescence in Jordan. Nevertheless, several actions were taken by company owners or businesses (Gao et al., 2020). The state can accelerate the growth of e-commerce, which includes the creation of e-government webpages, even though the majority of these services are beyond ideal. To put it another way, Jordan's government remains responsive to the growth of e-commerce.

Confidence is extremely important in both physical storefronts and e-commerce (Gheisari et al., 2021). There's little question that customers do not trust sellers, and they sense greater danger during the buyer journey (Pham et al., 2020). Trust, rather than innovation, encourages the establishment of e-commerce with all its manifestations, as early academics have stated. It is often assumed that popularity and review systems foster trust, allowing users to feel safe when making purchases via online e-commerce (Chandrasekaran et al., 2021; Manogaran et al., 2020). The term "smart logistics" refers to applying cutting-edge technology like blockchain and big data to warehouse operations. The conventional brand system encourages customers to rate vendors, receive suggestions after every purchase, and collect evaluations to create a brand value which can help customers decide whether or not to do business with a certain company (Fu et al., 2020).

The following are the achievements of this article:

- A generic paradigm for the consumer-to-consumer (C2C) e-commerce networks is proposed that addresses the slow response issue for recently licensed merchants.
- Students can analyze the smart logistics operation in e-commerce using bigdata and blockchain technology.
- To contribute, it employs the fuzzy DEMATEL technique in popularity forecasting.
- Reputation predictive ability is enhanced compared to popularity bootstrap approaches that use quality of service (QoS) characteristics during first reputation score allocation.

The Fuzzy DEMATEL approach evaluates the causes of construction-related accidents using fuzzy logic. This combo is used for the biased and inaccurate character of human judgment. In fuzzy numbers, angle sets are utilized instead of real statistics, and numbers are assigned to concepts with unclear meanings in the linguistic community. Several different technologies work together to ensure that elevated programs and data may be reliably executed on a system with reduced capability. To do this, QoS solutions provide distinct processing and distribution of network activity to particular flows.

The remainder of the article is as follows: Section 2 illustrates the background to the E-commerce systems. The proposed Students Consumption Behavior Approach (SCBA) is designed and implemented in section 3. Section 4 discusses the software analysis and implementation. Section 5 depicts the conclusion and future scope.

## BACKGROUND TO THE E-COMMERCE SYSTEMS

There have been a lot of studies looking at how students' consumption habits affect their results. They were not, however, faultless. The parameters of previous designs must be thoroughly examined to develop a new method. This study's findings will be compared to those from the prior one.

Predicting customer demand has gotten a lot of attention and research over the last few decades. Recommender system and material techniques were the two strategies. The recommender system, which included consumer and item-based techniques, implied that people who buy the same goods have comparable hobbies or tastes (Rehman et al., 2019). Users' tastes were often recorded in a subspace that preserves the evaluations they had provided. The user-based clustering algorithm assumed the likely rating provided by the potential customer to a specific item based on ratings or decisions to buy pasts of his comparable users (Sharma et al., 2021).

Similarly, the item-based pattern matching approach used comparable item evaluations or transaction data. The content-based technique predicts objects and people based on their descriptions (Gupta et al., 2018). Despite substantial research, data sparsity caused many prediction algorithms to perform badly, either in a cold-start circumstance. Contrary to the scarcity of information about a user's buying habits or reviews, information about a user's previous clicking activity on retail sites was plentiful. (Al-Khayyal et al., 2021) provided a framework for predicting consumers' interests based on their previous clicking behavior, which enhanced the accuracy of purchasing forecasting.

It has been demonstrated that user clicks forecast customer preferences while simultaneously avoiding data sparsity issues. However, because users' click activity records included much more information, it is important to think about retrieving meaningful information (Smaldone et al., 2021). In the beginning, features were solely used to describe what users had done to the products. Academics believe that consumers' tastes can be determined by what they have done to products, like hitting times and endurance durations. In truth, all these were a few characteristics that might reveal a user's interests. The essential aspects that impacted consumers' purchase decisions were the customer's and the product's personalities (Bucko et al., 2018) Ecommerce is the practice of buying and selling products and services online. Today, consumers can buy about everything online.

Sadly, the database did not always explicitly offer these letters; therefore, it must extract these from previous behavior data to create the shape of client and product symbols. The features extraction from user activity information has gotten attention lately, and many methods have been presented. (Loketkrawee et al., 2018) suggested that consumer, meeting, moment data, and not all essential information, like user ethnicity and sex, were collected from the customer data log. (Changchi et al., 2019) retrieved characteristics from the client's behaviors and product classification separately and their activities and interactions.

Yet, the research failed to consider the links between users' desire and their actions. Moreover, all of those study findings were predicated on the firm premise that if a customer chose to buy a specific product, that product was the one they had evaluated (Hwang et al., 2018). Consumers frequently choose many different things from the same category to contrast with the present item. Thus, while they were web users, they clicked many things simultaneously, demonstrating the customer's philosophy's choice and comparing procedures.

E-commerce, multi-agent, mentoring, and networking site platforms were a few of the computing science disciplines that had looked at brand management (Tan et al., 2018). Brand management assisted businesses in selecting a reliable and acceptable partner, reducing the chance of future faulty transactions. The majority of extant research focused on collecting customers' perceptions and promoting direct input. Yet, a few scholars had focused on the issue of reputational bootstrap.

The suggested system attributed newly installed applications to the service's ranking. The scholars evaluated provider reputation based on previous experiences. On the other hand, the methodology cannot deal with the supplier being a newbie throughout the reputation evaluation process. (Shamim et al., 2021) proposed the idea of preconception depending on partners' visible characteristics and actions.

By implementing slashing technologies and computerized systems, smart logistics can maintain a continuous flow of goods while minimizing costs. Following that, these preconceptions were used to assess the unidentified mates. This method was appropriate for fuzzy multi-agent companies that relied on agent collaboration.

For the first time, Zhou et al., presented the idea of marginal prestige value (Zhou et al., 2021). They integrated it with behavioral economics to prove the restriction of repute construction and resolve the prestige bootstrap issue. (Larson et al., 2018) used regression measures to estimate the repute ratings of newbie services by combining QoS characteristics with repute values of comparable services. (Soh et al., 2020) proposed a popular bootstrapping technique. Convolutional neural network (CNN) learns connections among QoS and reputes the quality of current services, which were then extended to calculate a repute score for previously unknown offerings.

However, the previous research did not explore selecting good reputation affecting elements from the cause of the issue and evaluating the internal linkages. (Kesharwani et al., 2020) employed hypothesis research. It measured a company's potential to create profits for clients by evaluating its charisma, supply chain, civic conscience, vision and management, work conditions, and personal wealth, among other factors to follow the behavior patterns of online shoppers. They incorporated all trust variables (client features, contacts, firm characteristics, and webpage architecture) with the origin of the confidence of the route model. Similarly, estimating a vendor's image in e-commerce was a difficult challenge. As a result, confirming which significantly influences prestige value in repute forecasting.

While smart logistics and business-to-business collaboration have grown rapidly, smart logistics ecological chain (SLEC) has emerged as a key tool for deploying circular supply chains (CSCI). CSCI at the SLEC was studied using a case study technique with four selected examples, and five factors influencing CSCI emerged. According to the findings, supply-demand matching (SDM) is improved by elements such as smart asset investment, multi-scenario service capabilities, and SLEC interaction. SLEC engagement and asset performance investing work together to improve the operating efficiency of the SLEC and increase customer engagement in CSCI, in addition to depending on SDM as an intermediate (Yan et al., 2022).

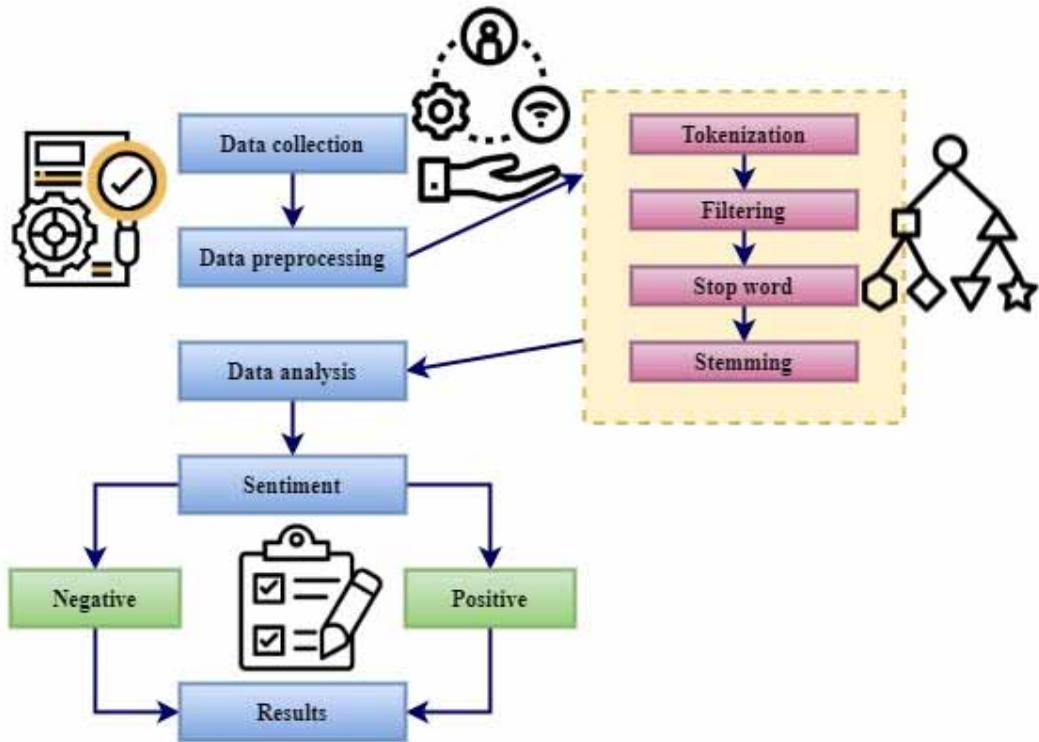
To examine and distribute E-commerce to college students, computer systems like CNN, RF, LDA, DT, SLEC and SVM cannot be used as indicated above. A fresh strategy called the Student's Consumption Behavior Approach (SCBA) is established to solve these challenges.

## **PROPOSED STUDENTS CONSUMPTION BEHAVIOR APPROACH**

The suggested system has two primary steps: first, create the model, and then effective mind text analytics on customer reviews utilizing our created prototype to give real-time statistics to users in an E-commerce platform, which is the major goal of this study. Reviews are remarks on an item to be good or bad and represent what individuals believe about it, and Star ratings and sentences are both acceptable forms of feedback.

The workflow of the proposed SCBA system is denoted in Figure 1. The data is collected and then preprocessed. The resultant data is analyzed, and the sentiment is analyzed positively and negatively. The processed data is tokenized filtered, and the words stem for better results. The suggested control structure for e-commerce applications employing a real-time text analytics model is used. Using Textual Information Labeling, phrases divided into words containing verbs, auxiliaries, and nouns are treated in the first stage. Because "good" is a descriptive word and "not nice" is a bad word, it used Negation stage detection and emotion study to find and analyze this statement. The construction model is discussed here, which aids in a greater grasp of the modeling process. It is the goal of smart logistics to employ integrated systems and data collecting to improve process management, maximize warehouse capacity and reduce operational costs in the facility. It is possible to sell products and services via the internet, known as e-commerce. Customers use electronic payments to make purchases on the company's website or online marketplace. Merchants ship or offer services after obtaining payment.

Figure 1. Workflow of the proposed SCBA system



With the rapid expansion of information in E-commerce, such websites are the primary source for users/customers to obtain reviews online to make purchasing decisions. The server-based solution provides real-time statistics on product information. It helps users make better decisions and save effort for consumers and providers by summarising user evaluations and deriving favorable or unfavorable thoughts. The software device was constructed in phase two, utilizing Python for the backend and Flask for RESTful.

Replace the precious data with identifiers and then have tokenization. As a general rule, most firms have data stored in their systems, such as credit card details, medical records or Social Security numbers. Fluids can travel through all the filters; however, the granules are trapped. The final product could be either the fluid that has been clarified or the solid particles that have been removed from the fluid. It is possible to identify a stop word as a phrase with the same probability of appearing in non-related texts as insignificant bits. A similarity metric can substitute the concept of relevance, as demonstrated in this study. When a word is reduced to its word stem, it is known as a syllable, or a suffix or prefix attached to a term's base.

## Methodology

Because Amazon is an e-commerce website, there are a lot of evaluations to be discovered there. For a classification algorithm, the information must be labeled, and the data obtained from Amazon, on the other hand, is unmarked and must be transformed to a labeled format.

## Data Collection

The sample in this research comes from a compilation of Amazon.com ratings and reviews. Every review comprises six pieces of data: the commenter's ID, the company's ID, the item's score, the

duration, the efficacy, and the customer reviews. The ranking can be discontinuous numbers, such as two stars, and not continuum values, such as 2.7 stars, with a range of 0 to 5. Amazon.com's Cosmetics and Musician Instrumentation reviews collected the information set for testing the system. Because the ratings are divided into one to 5 stars, it splits them to create the levels.

According to recent studies, student self-efficacy has increased academic performance, improved emotional health, and is a reliable indicator of both students' motivation. Incorporate relatively tough tasks Make use of other people's experiences. Encourage young people to have their interests as a source of inspiration for learning, make their own decisions, and provide them with targeted assessment and precise inferences.

## **Data Preprocessing**

The following steps are used for preprocessing the data collected.

- a) Tokenization attempts to break down an entire phrase into separate tokens such as symbols, keywords, and phrases. The comma is eliminated from some characters during tokenization, such as an exclamation mark.
- b) Reducing stop phrases: Stop phrases are those artifacts in a statement that aren't needed in any part of textual data, thus it generally removes them to improve assessment effectiveness. Punctuation is formatted differently in specific languages and regions.
- c) Parts of speech (POS) tagging: POS labeling is the method of allocating a phrase's syllable; it includes nouns, pronouns, verbs, adjectives, and their subclasses.
- d) Stemming: The act of combining modified variants of a term into a mutual understanding is known as stemming. It is a language processing approach for knowledge discovery public statements in texts.

Machine learning models are trained on raw data preprocessing to fit for use. Developing a machine learning model is the first and most important step. It is not always the situation that people have access to clean and prepared data when working on a machine learning project. Preprocessing data is essential to guarantee that it is of the highest quality. Data cleansing, data integration, data reduction, and data transformation are all parts of the preprocessing process, broken down into four phases to simplify things.

## **Sentiment Extraction & Tagging**

An impact on purchasing is defined as one that comprises at least one phrase that is either favorable or unfavorable. After removing Stop - word, screening, and stemmed terms like "in, that, is, are, thus, then," and thus on from the phrases transformed into symbols and used in POS tagger, the full evaluation would be tokenized into Common individual language.

POS labeling is a well-known and successful approach in computational linguistics for determining the function of phrases and organizing them depending on their utterance. The POS tagger is extremely useful for information extraction for two primary reasons:

- a) Names and adjectives, on average, do not include any feedback on products and services, which is readily deleted to use a POS tagging.
- b) A POS classifier too aids in distinguishing terms used during different sections of speech.

## **Negative Phrase Identification**

It is tough to evaluate the attributes of items from internet shopping since reviewers use various words, adjectives, and other terms. The bad prefixes recognize the real circumstance depending on nouns or verbs supplied by users. Take this comment from a lipstick purchaser: "Customer support mentality

is not incorrect; lipstick package feels lovely.” Because “wrong” is a derogatory word, “not wrong” evokes fewer or even more negative emotions.

There must be two phrases uncovered in the studies: negation-of-verb (NOV) and negation-of-adjective (NOA). As a result, identifying such sentences is difficult. To find such terms, it employed a negative polarization detection method.

It is possible to automatically flip the polarity of opinion words influenced by a negation using a technique known as “negative stage detection.” When they use the word “negation,” they refer to the part of the phrase that it affects. To be a decent person, consumers must be nice and helpful since it is right. Morally, a good deed is a correct thing to do. Wonderful person who goes out of her way to help those who are less fortunate. According to him, children should be taught to conduct good things as early as possible in life.

### Sentiment Classification

Information extraction is a method of assessing and interpreting subjective data from a large corpus of data (text). Sentiment categorizing, too known as polar classification, recognizes and classifies a certain viewpoint depending on its polarity (positive, negative, neutral). The support vector machine (SVM) Classifier segmentation model was employed for categorizing. Scikit-learn, a free software computer learning toolkit for Python, was utilized in this work. Python is a programming language to use for storage and analysis.

### Support Vector Machine

SVM is a guided learning approach for classifying either linear or nonlinear information. If the distribution is normal, the SVM looks for a kernel function which is a linear optimum separation subspace to divide various categories of information. Equation (1) represents a hyperplane that separates:

$$W \times T_r + B = 0 \tag{1}$$

$W$  is a weight matrix that can be  $W_1, W_2, \dots, W_m$ ,  $T_r$  is a learning tuple, and  $B$  is an integer. Equation (2) can be used to reduce the hyperparameters and simplification.

To better understand the spatial configuration of the data, one needs to create a spatial weights matrix. There are spatial correlations between the characteristics in the dataset that may be quantified using this method. To answer the question, I suppose that the image height of a tuple or a list is quite huge, and they are much more than likely to run out of space before they achieve a certain threshold. Items in a tuple could be of any kind, including integer, float, list, text, and thus on.

$$\sum_{x=0}^m \beta_x \times o_x \times T_{r(x)} = 1 \tag{2}$$

The numeric variables, tags, and weight vector are denoted by  $\beta_x$ ,  $o_x$  and  $T_{r(x)}$ , correspondingly. Equation (2) ‘s the outcome is determined by  $o_x$ , as stated in Equations (3) and (4)

$$\sum_{x=0}^m W_x \times o_x \geq 1 \text{ if } o_x = 1 \tag{3}$$

$$\sum_{x=0}^m W_x \times o_x \geq -1 \text{ if } o_x = -1 \quad (4)$$

The weight factor is denoted  $W_x$  and the outcome of the system is denoted  $o_x$ . When dealing with linear regression information, the SVM first employs a mapping function to transfer the transformed data, then solves the issue using an SVM. These factors are termed as kernel trick, and the Gaussian Radial Basis Set (RBS) is most commonly utilized, which is represented using Equation (5):

$$L(T_{r(x)}, T_{r(y)}) = \exp \left( -\beta \left[ \frac{T_{r(x)} - T_{r(y)}}{2} \right]^2 \right) \quad (5)$$

$T_{r(x)}$  and  $T_{r(y)}$  accordingly coordinates and assessment tuples then is a free variable that utilizes the Scikit-learn utility for Python's default settings. The learning rate is denoted  $\beta$ .

As an example, a Kernel Trick is an easy way of categorizing quasi data that may be split by a plane using a higher-dimensional projection of the data. Radical Basis Sets (RBS), which are true functions, are defined by the distance between the input and a constant value (the origin or another location known as the center). A radial functional is any value that meets the criteria. If two points in the dataset are close together, the angles between the matrices that reflect them in the kernel space will be small. The Gaussian kernel translates linear combination into the Gaussian function of the distance between points in the dataset.

### Reputation Estimation

The machine learning algorithm is a statistical method system that includes a hardware device to replicate the form and composition of a neuronal structure. It is made up of numerous intake and output data cells that are linked as per particular topological features. Due to its capacity to solve nonlinear and complicated system issues, the backpressure (BP) model is frequently utilized in regress, identification, and forecast research. It offers benefits for addressing ambiguous and erroneous data problems while incorporating numerous elements. The three-layer BP was shown to realize arbitrary nonlinear translations in theory. As a result, it is used in this system to understand the connections among the reputational scores.

First, the link weight, cutoff, and support vectors are used to determine the desired value. The network weights and limits are adjusted given the disparity between the actual output and the goal value. The learning procedure is continued until the mean squared error (MSE) value falls below a predetermined threshold. The starting settings of the network parameters and limits are important for the training phase, then they have no impact on the quality of training. Starting weights are calculated at randomness in this suggested model, and thus all cells have a sigmoid function, and it is expressed in Equation (6):

$$g(p) = \frac{1}{1 + \exp(-p)} \quad (6)$$

Tuple ( $V_1$ ) is the input image, representing the previous phases obtained. The associated reput score is the output variable. The training examples and testing datasets are related to the existent

entities, and the brain is fully trained using the important variable BP method. Equation (7) is used to standardize input variables and corresponding outputs to allow faster artificial neural instruction:

$$O^* = \frac{O - \min(O)}{\max(O) - \min(O)} \quad (7)$$

The output variable is denoted  $O$ , the minimum and maximum functions are denoted *min* and *max*.

Angular displacements are the maximum and minimum values of a function, whether inside a selected timeframe or in the solution domain, in the context of quantitative equations. On the other hand, the predicted output refers to the column or row that one may not always have and wants to anticipate subsequent input information. The term “response variable” is sometimes used.

The pictorial representation of  $O^*$  is depicted in Figure 2. It uses the minimum and maximum function of the outcome functions. It is worth noting that several of the requirements have inverted values. As a result, the normalized value ( $V_1$ ) is denoted in Equation (8)

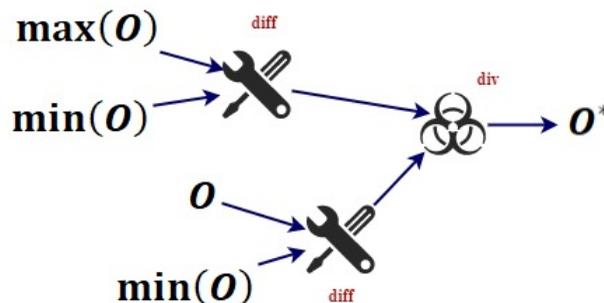
$$O^* = 1 - \frac{O - \min(O)}{\max(O) - \min(O)} \quad (8)$$

The output variable is denoted  $O$ , the minimum and maximum functions are denoted *min* and *max*. It employs a quick optimization approach known as the Levenberg-Marquardt (LM) method, which uses the continuity formula to update the weights of the connections and limits repeatedly. The predicted result is denoted in Equation (9)

$$p(n+1) = p(n) - \frac{(L^T L + \varphi I)^{-1} L^T}{r} \quad (9)$$

$p(n)$  are the  $n$ th iteration’s major impact and limit vector,  $L$  is the Jacobian structure of the first variant of the artificial neural mistake to the weight vectors and threshold values, and a seems to be the deciding factors that should be decreased after an effective recursion (i.e., the mistake declines)

Figure 2. Pictorial representation of  $O^*$



and enhanced if the mistake rises. The identification matrix is  $I$ , while the mistake vector is  $r$ . Continue the cycle of learning till the MSE is less than 0.0001.

It is important because the Jacobian is the best linear approximations to a differentiable function near a particular point. A multidimensional function's Jacobian is the stored procedure derivative in this sense. In applied mathematics and, for example, in Relativity Theory, Jacobian matrices are employed to investigate variations in the foundation. For example, Jacobian matrices are employed in applied mathematics to examine changes in the basis.

The pictorial representation of the predicted result is denoted in Figure 3. It uses the Jacobian, identity matrix, and other functions to calculate the predicted results.

### Proposed Model

Motivated by earlier research, it focuses on extracting features problems from user activity logs and then utilizes the Bayes classifier model in data gathering to forecast purchase patterns in shopping websites. It used Ali Mobile Suggestion Contest information in 2017 to assess the hypothesized technique, which comprised behavior logs of products from phone devices over a month from June 18, 2013, to July 19, 2017.

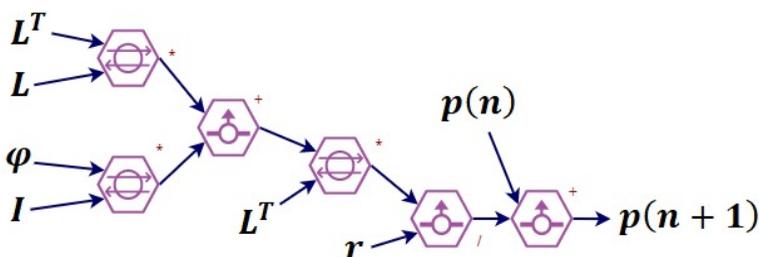
#### User Click Behavior Analysis

It must extensively investigate the correlations between customers' click activity and buying behavior by studying various statistical information to produce relevant and effective categorization features. A session is defined as all of the actions performed by the same client on the same object and is identifiable by the consumer pair. First, it looks at a few features that the database has in common and sees how people act while purchasing. It discovered this because when consumers want to buy something, they are considerably more likely to engage than if they have little curiosity about the product or are dissatisfied.

Consumer Buying Behavior refers to the behavior made by customers before buying an item (both online and offline). A range of activities, such as using search engines or responding to messages on social media, may too be part of this procedure. For marketers to grasp the expectations of their customers, they must study consumer purchasing habits. An understanding of what motivates customers to purchase products is useful. Before releasing them to the marketplace, companies must know what kind of goods consumers prefer.

The customer's overall click behavior amount is much more than five times in 70.3 percent of buy sessions, whereas 7.5% of non-purchase meetings had the same click behavior number. It suggests that predicting customers' purchases based on actual click activity figures would be beneficial. A user clicks on an item on several occasions before buying a product, and a customer clicks on a mean nine times before buying a product in the given data. The primary Information retrieval method failed to use this browsing history, which tracks how users engage with structure and provides transactions.

Figure 3. The pictorial representation of the predicted result



It discovered that when a customer is willing to purchase on an acceptor site, he is more inclined to spend there. As a result, the overall number of views and the length of a transaction could be used to gauge a user's overall attitude about online buying. It too discovered various user characteristics, such as how frequently the customer would buy the product, how often the customer would select the product on averages when buying a product, etc. These characteristics do not reflect direct interactions between the client and the object, they might reveal the user's typical purchasing behaviors and tendencies. It can acquire them via user behavior statistical log information.

The system design of the proposed SCBA system is shown in Figure 4. It has a server model and a development model. It uses a python system, web pages, and database in the server, and the development model uses data cleaning, training model, and serialized model. The characteristics of the things themselves are comparable. It does not have facts from the real data, like product title, cost, or revenue. It can acquire important material from the product's national statistics, like how many instances the product has been selected, put to the checkout process, and bought.

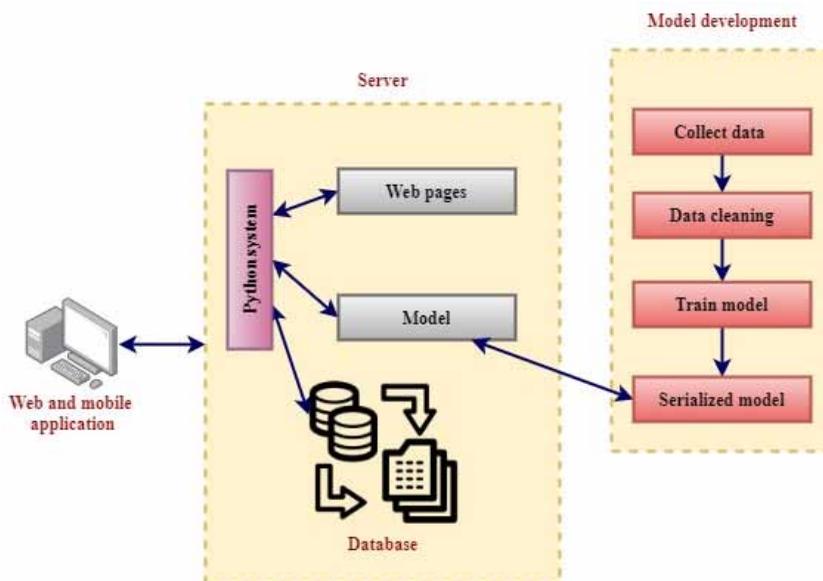
It examined the purchase behaviors in varying periods to identify the correlations between browsing time and buying behavior. The likelihood of purchasing anything changes dramatically over time. As a result, buying behavior is closely connected with the customer's last visiting time, and purchasing intention decays as time passes. As per the experts, this is realistic. People are more likely to purchase products they have seen recently instead of items they have seen previously. Using this data retrieves the hours as a character from the moment the user clicks the product.

### Feature Extraction

It creates the characteristics from the following factors, depending on the view above and past works:

- 1) For customers, it provides elements representing their purchasing habits, preferences, and routines, like adding items to a cart before buying a product or clicking more than nine times before buying a product.
- 2) Characteristics for things are those that indicate the intrinsic quality of each item, such as the frequency of customers, click behaviors and buying habits that have occurred.

Figure 4. The system design of the proposed SCBA system



- 3) For the meetings, concentrate on the customer's recent behaviors on this object. That reflects their means to purchase or not, like how many hours the consumer has perused the product, how often the consumer has decided to add the product to his favorites, or how many hours the consumer has created the product to his cart.
- 4) In terms of time, it created features such as the clicks per 60 minutes, the first (fortnight, day, and mins), and the last time the person clicked the product. The variety of once to the consumer pressed the product, the average button amount in every timeframe and the mean increment among two adjoining time frames.
- 5) Characteristics for the subcategories capture the connections among users, objects, and the related item classes. The characteristic of a customer's average amount spent on a particular product category, for instance, might disclose the customer's affinity for that inventory item. The difference in click counts between the supplied product and other things in the same class might reveal why the customer chose this item over people in a similar area.

Furthermore, these criteria expanded to various periods to get additional purchase forecasting characteristics. Both Binary and real-valued component packages were frequently employed in classification issues. The feature value in a binary-valued characteristic type has to be either 1 or 0, notifying whether a specific phenomenon happens during the period. The periodicity, calculated as the number of times a certain click behavior occurred in a real-valued characteristic model, is commonly called characteristic. It turns these statistical data into rational design and features a Bayesian inference strategy to use these relevant features.

### *Sentiment Analysis Model Development*

The algorithm for sentiment classification is created and then implemented into an E-commerce system. During the study for this work, the Natural Language Toolkit (NLTK) was employed and the Python Scikit-learn module for SVM construction. SVM is one of the most straightforward classifications and has the best accuracy, which is why it chose it for our study. It explained the pattern creation technique in the approach step above to get the best reliability of outcomes.

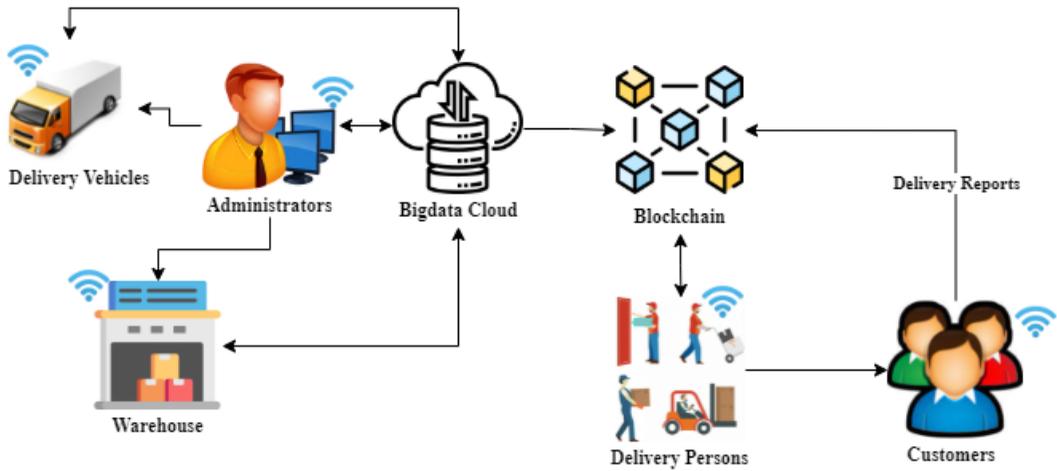
The NLTK corpus collection comprises texts with pro and con polarity scores employed to fit the classifier, subsequently assessed using the public library SVM. The pauses words recognized in the phrases are likewise stored in the corpus collection. All loaded JSON files are dumped into pickle folders for a quicker recovery. The records contain scores between one and five stars; thus it deleted the three-out-of-five score to make it impartial comments, and it wants the lesser or greater for a pro or con feedback. The purpose of this article is to analyze customer reviews, forecast the rating, and display the total pro and con proportion of the feedback in live time; thus, it serialized the system after evaluating it to utilize it in the program. Serialization is storing an item instance's information to a storage device.

### *Smart Logistic Technologies Using Bigdata And Blockchain*

College students analyze the smart logistics in e-commerce platforms using bigdata and blockchain technology, as shown in figure 5. The bigdata cloud stores the data from all the back offices and administrative offices. The blockchain technique is employed to ensure the security of the full online processes starting from warehouse to customers. Smart logistics encourage automated handling machinery or robots to perform the most repetitive operations, such as moving items, inserting and retrieving unit loads and order fulfillment.

$$O = \cos \left( \frac{1}{\log(P)} \right) * \log \left( \frac{V}{P} \right) * P(\sqrt{V}) \quad (10)$$

Figure 5. The smart logistic technology



$$C = \sqrt{|O(u)|^2} \frac{O}{u} \sqrt[3]{O} \tan(f \varnothing^2 - 1) \quad (11)$$

$$S = \sqrt{P(v) \gamma(v) \Pi F\left(\frac{1}{v}\right) \gamma v(\varnothing)} \quad (12)$$

As per equations 10, 11, and 12, output in electronic information  $O$  is the  $\cos$  measure of trigonometric action for logarithmic dataset  $\log(P)$  Logarithmic division of emails in their totality  $V$  with dataset  $P$  and dataset multiplied with root value of emails in their totality  $V$ . The conveyance of goods  $C$  is the computation of output in electronic information  $O$ ; for the quality of providers  $u$ ,  $\tan$  is the original problem trigonometry function multiplied with the duration of time it took to locate the problem  $\varnothing^2$  integrated and subtracted. The successful delivery rate  $S$  is the root value of several dataset  $P$ , a tool for image data  $v$  then double integral of a location's algebraic structure  $\gamma(v)$ , the function of the tool for image data  $\frac{1}{v}$  A framework for monitoring systems  $\gamma$  and the time it took to locate the problem  $\varnothing$ .

The proposed SCBA system is designed and analyzed in this section—the proposed SCBA system with fuzzy logic and a machine learning model. The proposed system will help college students learn about smart logistic technologies. The smart logistics system is handled by bigdata and secured by blockchain technology, and it improves the successful delivery rate compared with other techniques.

## SOFTWARE ANALYSIS AND PERFORMANCE

The studies leverage a real-world statistical model supplied by Ali Mobile Suggestion Contest in 2017 to evaluate the technique for consumer purchasing forecasting. The instruments collected 12 million activity records from 12,000 users over 2.8 million products for one month. Each behavior record represents a user's click behavior on a specific item and includes the user ID, product ID, item classification, behavior type, day, and hour (exact to the hour). There are four different types of behavior: 1, 2, 3, and 4. The first is for exploring, the second is for saving to favorites, the third is for putting to the cart, and the fourth is for paying. The trials group all user actions related to the same product into transactions identifiable by a user-item combination. Suppose indeed the client

has bought the product. In that case, the sessions will be labeled with the letter 'Y,' otherwise, it is labeled with the letter 'N.' The amount of paid and non-purchased visits in this given data, on the other hand, is significantly uneven, with around four times fewer of each. As a result, it chose the same number of non-bought experiences as paid sessions to create the next range of data to examine.

Figures 6 and 7 show the accuracy and precision of the proposed SCBA system, respectively. The simulation outcomes of the proposed SCBA system is analyzed using the given dataset, and the outcomes are compared with the existing models such as convolutional neural network (CNN), random forest (RF), linear discriminant analysis (LDA), decision tree (DT), and support vector machine (SVM). As the simulation time varies, the respective simulation outcomes of the proposed SCBA system too increase. The proposed SCBA system with a consumption analysis model exhibits higher results.

Table 1 indicates the simulation outcome analysis of the proposed SCBA system. The simulation outcomes, such as the accuracy and precision of the proposed SCBA system, are analyzed, and the results are compared with the existing models like CNN, RF, LDA, DT, and SVM. The simulation analysis is carried out by varying the given number of samples from minimum to a maximum value, and the respective simulation outcomes are compared. The proposed SCBA system with machine learning and prediction model exhibits higher simulation findings than the existing models.

Figures 8 and 9 show the F score and specificity analysis of the proposed SCBA system, respectively. The proposed SCBA system is analyzed concerning the given dataset. The simulation is carried out by changing the given number of samples from the minimum to the maximum. The respective F score and specificity of the proposed SCBA system are analyzed. The results are compared with the existing models. The proposed SCBA system with machine learning, fuzzy model, and consumption behavior mode products shows better simulation results than the existing models.

Table 2 indicates the error analysis of the proposed SCBA system. The system error in terms of root mean squared error (RMSE) and mean absolute peak error (MAPE) of the proposed SCBA system are calculated and tabulated. As the number of iterations increases, the respective simulation outcomes of the proposed SCBA system increase. The proposed SCBA system with a fuzzy system simplifies the construction process and produces faster results than the existing models. The proposed SCBA system with machine learning and consumption prediction model exhibits higher results.

The root means squared error (RMSE) and means absolute peak error (MAPE) analysis of the proposed SCBA system are depicted in Figures 10 and 11. The simulation analysis of the proposed

Figure 6. Accuracy analysis of the proposed SCBA system

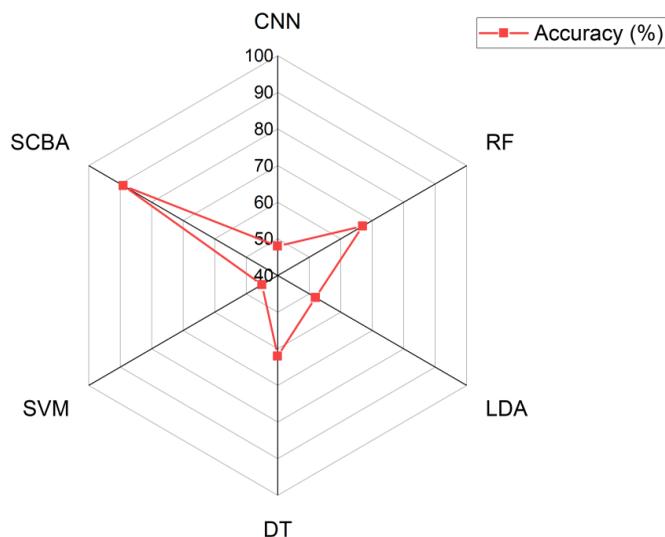


Figure 7. Precision analysis of the proposed SCBA system

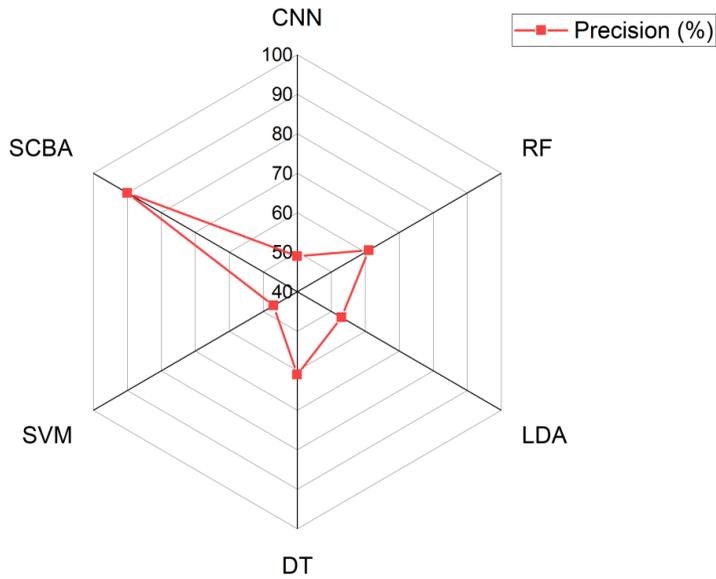


Table 1. Simulation outcome analysis of the proposed SCBA system

| Method | Accuracy (%) | Precision (%) |
|--------|--------------|---------------|
| CNN    | 48           | 49            |
| RF     | 67           | 61            |
| LDA    | 52           | 53            |
| DT     | 62           | 61            |
| SVM    | 45           | 47            |
| SCBA   | 89           | 90            |

Figure 8. F score analysis of the proposed SCBA system

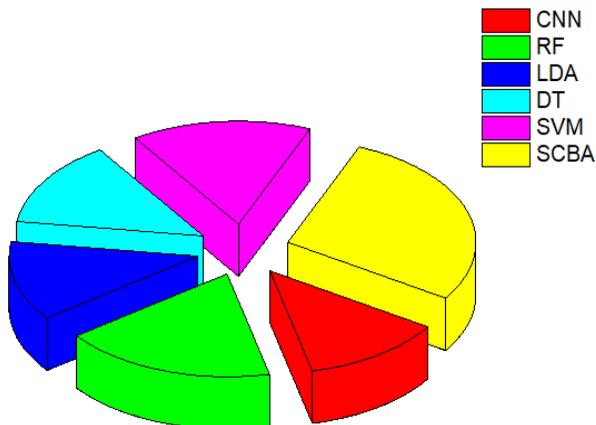


Figure 9. Specificity analysis of the proposed SCBA system

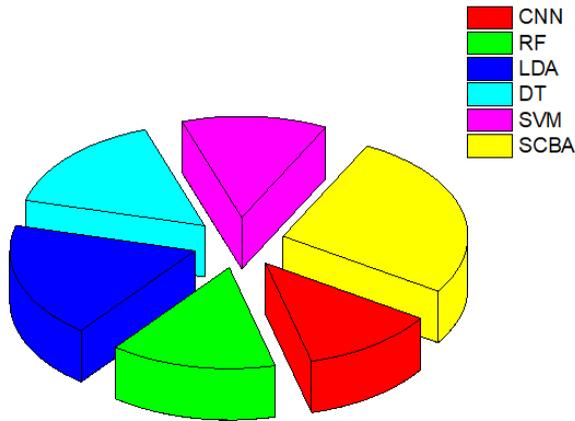


Table 2. Error analysis of the proposed SCBA system

| Method | RMSE (%) | MAPE (%) |
|--------|----------|----------|
| CNN    | 24       | 26       |
| RF     | 29       | 31       |
| LDA    | 35       | 38       |
| DT     | 27       | 29       |
| SVM    | 36       | 34       |
| SCBA   | 12       | 13       |

Figure 10. RMSE analysis of the proposed SCBA system

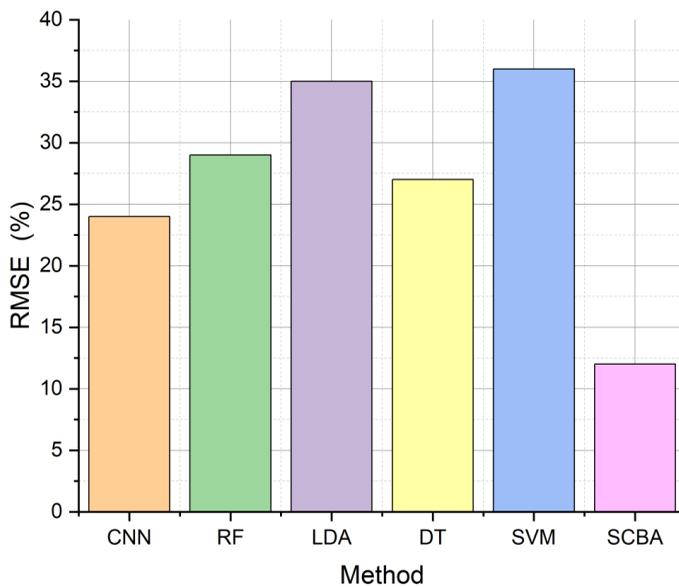
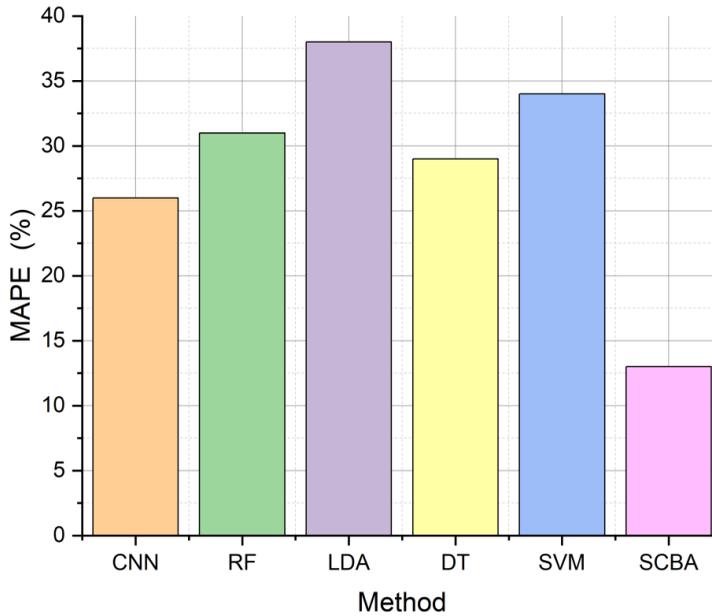


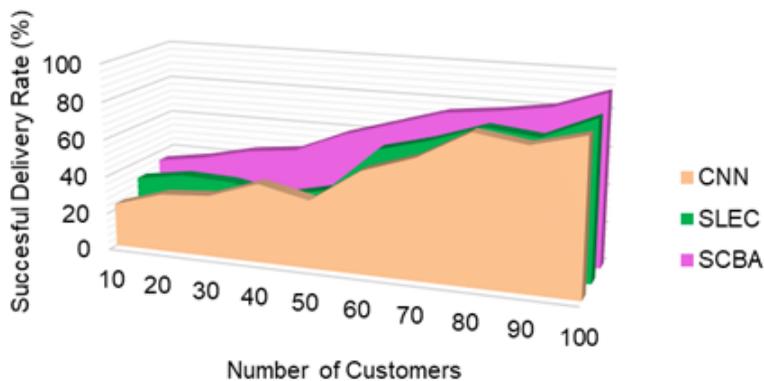
Figure 11. MAPE analysis of the proposed SCBA system



SCBA system is done by considering the number of samples from the given dataset. As the sample size increases, the respective learning rate in the machine learning model increases, resulting in higher simulation results in lower RMSE and MAPE. The proposed SCBA system with machine learning and prediction models performs the existing models.

Experts call the distribution rate the proportion of emails received to the total number of messages sent. The delivery rate is the ratio of emails received to emails sent divided by the number received. Any communication that does not get transmitted is referred to as a “bounce” in this context. Its delivery performance can gauge the supply chain’s ability to deliver items and services to customers. Logistics management relies heavily on this indicator since it encompasses the entire value chain, the provider to the user. Figure 12 shows that the successful delivery rate may be analyzed using Equation 12, which has a higher success rate than other techniques.

Figure 12. Analysis of successful delivery rate



The proposed SCBA system is analyzed, evaluated and the outcomes are compared with the existing models. The simulation analysis of the proposed SCBA system exhibits higher simulation findings than the existing models with the help of machine learning, fuzzy system, and consumption prediction model.

## **CONCLUSION AND FUTURE SCOPE**

This article discovered that most online consumers were college participants who bought clothing items online, their preferred platform. Male students mostly used E-commerce to purchase gadgets. Given the small random sample, the normal method could not be used. The student's Consumption Behavior Approach (SCBA) is suggested in this article. The proposed SCBA system research revealed three variables that severely affect college students' purchase behavior: pleasure, risk, and social power. Grouping the features of learners has been done to define the precise focus of the students' sector as a prospective market. It was discovered that there would be three separate segments connected to online buying behavior using the proposed SCBA system to group the learners. Online buying is impacted by social impact and the sense of danger for section one. The choice to purchase online is impacted by pleasure and the attractiveness of the webpage for sector two. The proposed SCBA system enhances the accuracy 89%, precision 90%, and successful delivery rate 91.3%; it reduces the root mean squared error 12% and mean absolute peak error 13%.

This research is on the site's functionality and trustworthiness, and protection. These findings are the outcome of a Chinese survey. Because the features and habits of Chinese college students are likely to be comparable, the findings can be extrapolated to a broad university population in China. The analysis approach can be used in various situations when the sample group is restricted in the future. Colleges and universities can use this model to guide students to improve their understanding of the new consumption pattern, establish a scientific and systematic consumption view, and guide students to correct the current consumption behavior, mode and content. On the other hand, in an era of mass entrepreneurship and innovation, cross-border e-commerce has pointed out a new direction for college students to innovate and start their businesses. Therefore, colleges and universities can offer some courses or lectures on cross-border e-commerce; the new shopping environment and mode provide college students with a new choice for employment and entrepreneurship.

## REFERENCES

- Al-Khayyal, A., Alshurideh, M., Al Kurdi, B., & Salloum, S. A. (2021). Factors influencing electronic service quality on electronic loyalty in online shopping context: data analysis approach. In *Enabling AI Applications in Data Science* (pp. 367–378). Springer. doi:10.1007/978-3-030-52067-0\_16
- Amudha, G., & Narayanasamy, P. (2018). Distributed location and trust based replica detection in wireless sensor networks. *Wireless Personal Communications*, 102(4), 3303–3321. doi:10.1007/s11277-018-5369-2
- Bucko, J., Kakalejčík, L., & Ferencová, M. (2018). Online shopping: Factors that affect consumer purchasing behavior. *Cogent Business & Management*, 5(1), 1535751. doi:10.1080/23311975.2018.1535751
- Burns, D. J., Gupta, P. B., Bihn, H. C., & Hutchins, J. (2018). Showrooming: An exploratory empirical investigation of students' attitudes and behavior. *Information Systems Management*, 35(4), 294–307. doi:10.1080/10580530.2018.1503802
- Chandrasekaran, G., Nguyen, T. N., & Hemanth, D. J. (2021). Multimodal sentimental analysis for social media applications: A comprehensive review. *Wiley Interdisciplinary Reviews. Data Mining and Knowledge Discovery*, 11(5), 1415. doi:10.1002/widm.1415
- Changchit, C., Cutshall, R., Lonkani, R., Pholwan, K., & Pongwirithon, R. (2019). Determinants of online shopping influencing Thai consumers' buying choices. *Journal of Internet Commerce*, 18(1), 1–23. doi:10.1080/15332861.2018.1496391
- Fu, H., Manogaran, G., Wu, K., Cao, M., Jiang, S., & Yang, A. (2020). Intelligent decision-making of online shopping behavior based on the internet of things. *International Journal of Information Management*, 50, 515–525. doi:10.1016/j.ijinfomgt.2019.03.010
- Gao, J., Wang, H., & Shen, H. (2020). Task failure prediction in cloud data centers using deep learning. *IEEE Transactions on Services Computing*.
- Gheisari, M., Najafabadi, H. E., Alzubi, J. A., Gao, J., Wang, G., Abbasi, A. A., & Castiglione, A. (2021). OBPP: An ontology-based framework for privacy-preserving in IoT-based smart city. *Future Generation Computer Systems*, 123, 1–13. doi:10.1016/j.future.2021.01.028
- Gunasekaran, A., & Narayanasamy, P. (2018). Analyzing the Network Performance of Various Replica Detection Algorithms in Wireless Sensor Network. *Journal of Computational and Theoretical Nanoscience*, 15(3), 989–994. doi:10.1166/jctn.2018.7188
- Hwang, Y. M., & Lee, K. C. (2018). Using an eye-tracking approach to explore gender differences in visual attention and shopping attitudes in an online shopping environment. *International Journal of Human-Computer Interaction*, 34(1), 15–24. doi:10.1080/10447318.2017.1314611
- Kesharwani, S., & Sharma, N. (2020). Swaying between qualitative information and customers' expectation: An assessment of online shopping sites in India. *International Journal of Information Technology*, 12(3), 789–795. doi:10.1007/s41870-019-00414-7
- Larson, L. R., & Shin, H. (2018). Fear during a natural disaster: Its Impact on perceptions of shopping convenience and shopping behavior. *Services Marketing Quarterly*, 39(4), 293–309. doi:10.1080/15332969.2018.1514795
- Loketkrawee, P., & Bhatiasevi, V. (2018). Elucidating the behavior of consumers toward online grocery shopping: The role of shopping orientation. *Journal of Internet Commerce*, 17(4), 418–445. doi:10.1080/15332861.2018.1496390
- Manogaran, G., Alazab, M., Saravanan, V., Rawal, B. S., Shakeel, P. M., Sundarasekar, R., Nagarajan, S. M., Kadry, S. N., & Montenegro-Marin, C. E. (2020). Machine learning assisted information management scheme in service concentrated iot. *IEEE Transactions on Industrial Informatics*, 17(4), 2871–2879. doi:10.1109/TII.2020.3012759
- Nayyar, V., & Batra, R. (2020). Does online media self-regulate the consumption behavior of INDIAN youth? *International Review on Public and Nonprofit Marketing*, 17(3), 277–288. doi:10.1007/s12208-020-00248-1

- Pham, D. V., Nguyen, G. L., Nguyen, T. N., Pham, C. V., & Nguyen, A. V. (2020). Multi-topic misinformation blocking with budget constraint on online social networks. *IEEE Access: Practical Innovations, Open Solutions*, 8, 78879–78889. doi:10.1109/ACCESS.2020.2989140
- Rehman, S. U., Bhatti, A., Mohamed, R., & Ayoup, H. (2019). The moderating role of trust and commitment between consumer purchase intention and online shopping behavior in the context of Pakistan. *Journal of Global Entrepreneurship Research*, 9(1), 1–25. doi:10.1186/s40497-019-0166-2
- Shamim, K., Ahmad, S., & Alam, M. A. (2021). COVID-19 health safety practices: Influence on grocery shopping behavior. *Journal of Public Affairs*, 21(4), 2624. doi:10.1002/pa.2624 PMID:33786020
- Sharma, S. (2021). Modeling the role of information on the spread of online shopping. *Computational and Mathematical Methods*, 3(5), e1182. doi:10.1002/cmm4.1182
- Smaldone, F., D'Arco, M., Marino, V., & Pellicano, M. (2021, April). Brave Consumers for a New Digital World: Exploring Online Shopping Motives During Covid-19. In *The International Research & Innovation Forum* (pp. 425–433). Springer.
- Soh, P. Y., Heng, H. B., Selvachandran, G., Anh, L. Q., Chau, H. T. M., Son, L. H., Abdel-Baset, M., Manogaran, G., & Varatharajan, R. (2020). Perception, acceptance, and willingness of older adults in Malaysia towards online shopping: A study using the UTAUT and IRT models. *Journal of Ambient Intelligence and Humanized Computing*, ●●●, 1–13. doi:10.1007/s12652-020-01718-4
- Tan, G. W. H., & Ooi, K. B. (2018). Gender and age: Do they really moderate mobile tourism shopping behavior? *Telematics and Informatics*, 35(6), 1617–1642. doi:10.1016/j.tele.2018.04.009
- Yan, X., Liu, W., Lim, M. K., Lin, Y., & Wei, W. (2022). Exploring the factors to promote circular supply chain implementation in the smart logistics ecological chain. *Industrial Marketing Management*, 101, 57–70. doi:10.1016/j.indmarman.2021.11.015
- Zhao, Y., Yu, Y., Shakeel, P. M., & Montenegro-Marin, C. E. (2021). Research on operational research-based financial model based on e-commerce platform. *Information Systems and e-Business Management*, 1-17. doi:10.1007/s10257-021-00509-44
- Zhou, M., Huang, J., Wu, K., Huang, X., Kong, N., & Campy, K. S. (2021). Characterizing Chinese consumers' intention to use live e-commerce shopping. *Technology in Society*, 67, 101767. doi:10.1016/j.techsoc.2021.101767