Using Fuzzy Clustering Models to Predict User Demand in Precision Marketing of Cross-Border E-Commerce

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Abstract: *Based on increasing user demands, domestic e-commerce transactions are encouraged across international borders. A product/service demand forecast is necessary to improve the transaction rate for stagnancy-less returns. Though different methods have been employed to forecast user demands, this article introduces a different proposal using fuzzy C-means clustering. It is named as Iterative C-means Clustering Method (ICCM), in which the returns based on transaction and goods stagnancy are separated. The clustering process is iterated throughout the transactions to differentiate the above and identify the actual demand across borders. Using this differentiation, the demand that defaces the returns is classified through minimum degree of stagnancy. Such identified process retards the cross-border transaction for false user demand forecasts, ensuring the goodwill of the products/services. The fuzzy-based derivative groups are disintegrated post the transaction completeness to improve the prediction efficacy*.

Keywords: *Cross border, e-commerce, fuzzy c-means, stagnancy degree*.

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1. Introduction

Market demand forecasting in cross-border e-commerce is vital for managing operations, optimizing inventory, and maximizing revenue. Accurate demand prediction relies on data-driven insights derived from financial transactions, logistics, and consumer behavior patterns [24]. By using historical transaction data and predictive models, businesses can proactively anticipate demand fluctuations, allowing for strategic adjustments in supply chain management and marketing initiatives [4]. Advanced machine learning techniques, such as Fuzzy C-Means (FCM) clustering, play a crucial role in dynamic segmentation of consumer purchasing behavior. The diversified research on e-commerce logistics, fraud detection, and consumer behavior provides insights for refining the predictive models. Cloud storage technology, a robust predictive dashboard backbone with high accuracy and timeliness in demand forecasts, enhances these features [34]. Besides, studying consumer switching intentions and promotional strategies helps in fine-tuning predictive models. Regulations such as the General Data Protection Regulation (GDPR) must also be considered while conducting big data analytics in e-commerce [35]. Using emotional correlation analysis and the user keyword-driven correlation graph search helps discover user groups and improve recommendation systems [2].

Identifying false market demands in cross-border e-commerce using return data is important for businesses to maintain credibility and profitability [1]. Analyzing return data through clustering-based anomaly detection techniques, including FCM, aids in distinguishing genuine demand from manipulative purchasing activities [21]. The analysis is crucial to maintaining market integrity and customer trust. Mitigating false demand involves re-engineering product offerings, improving quality control measures, and raising the bar on fraud detection [25]. Partnering with logistics partners and sophisticated artificial intelligence-driven systems is central to detection efforts [19]. Demographic research of customer behavior facilitates forecasting market manipulation and preparing response strategies. Through proactive measures and technological innovation, businesses can strengthen their global e-commerce position, assuring sustainable growth and customer satisfaction. Continuous strategy review and adaptation to emerging trends are indispensable in a dynamic, cross-border e-commerce landscape [27, 28].

Return validation optimization techniques are indispensable for meaningful business intelligence and a profitable cross-border e-commerce business [36]. Data analytics and machine learning help identify the patterns of fake market demand. Real-time monitoring of the market dynamics enables timely adjustments to the validation criteria of the returns [8]. The validation processes are aligned with promotion, enhancing accuracy in assessing market demands. Robust data governance practices heighten the reliability of the validation outcomes [13]. These optimization techniques reduce financial losses and improve customer satisfaction. Integrating market demand insights speeds adaptation to consumer preferences. Logistics partnership collaboration strengthens the validation strategies [9]. Continuous refinement of techniques makes the validation processes efficient. The use of technological advancements empowers businesses to remain competitive. Strategic alignment of validation with market demands fosters resilience in operations. Optimization based on market demand fosters long-term sustainability in e-commerce [26, 37].

The main objective points are:

- To introduce the Iterative C-means Clustering Method (ICCM) for forecasting user demand in cross-border e-commerce using fuzzy C-means clustering to distinguish between returns based on transactions and goods stagnancy.
- To identify and reduce false user demands in cross-border e-commerce transactions by iterative clustering and analyzing transaction and stagnancy data to improve demand forecasts.
- To evaluate the performance of the ICCM method in predicting demand and detecting stagnancy across four product categories: electronics, consumables, decors, and clothing.

The ICCM for cross-border e-commerce demand forecasting is introduced in this paper. Subsequently, it isolates transaction and product stagnancy returns to reduce misleading demand. The study incorporates goods stagnancy analysis into demand forecasting to fully understand demand patterns. Prediction accuracy is improved by fuzzy derivative grouping and deconstructed post-transaction. The approach is tested across four product categories to show adaptability and reveal cross-border e-commerce demand forecasting disparities.

Table 1. Contribution summary.

Aspect	Method/Approach	Status	Source/Reference	Contribution
Methodology	ICCM	Implemented	Section 3.2 of this study	Introduces ICCM to enhance user demand prediction accuracy in cross-border e-commerce.
Clustering	Fuzzy-based clustering	Implemented	Section 3.2 of this study	Uses fuzzy logic to improve adaptability in demand segmentation and reduce uncertainty.
Data analyses	External data sources	Performed	Product demand forecasting e-commerce sales forecast	Uses real-world datasets to validate the proposed clustering method for demand forecasting.
Discussion	5 Metrics with 4 influences	Performed	Section 5 of this study	Evaluates demand prediction effectiveness using five key performance metrics and four influencing factors.

The contributions are summarized in Table 1 obve.

2. Related Works

Yang *et al*. [33] studied Alibaba.com seller satisfaction, a popular online business platform for cross-border trade. The method aims to determine the factors influencing enterprise sellers' satisfaction with Alibaba.com. The data was collected from 184 respondents of enterprise sellers and analyzed using Smart Partial Least Squares (PLS) to determine these factors. This method gives an insight into how to enhance customer satisfaction among the sellers at Alibaba.com. Xu *et al*. [32] proposed a study on how social commerce affects consumer engagement. The method aims to understand how Cross-Border E-Commerce (CBEC) consumers address challenges using social platforms. Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) determine if motivation, opportunity, ability, involvement, and purchase intention are related online. The method provides insights into CBEC consumers' adoption of social platforms indicating e-commerce and consumer behavior trends.

Luo *et al*. [17] introduced a method for understanding the reputation trap in Chinese e-commerce. The technique aims to understand how this trap works and how companies use product strategies to reduce its impact. The method may employ statistical analysis such as regression to see if there is any relationship between online reputation, firm survival, and product strategies like pricing or variety. The approach provided supportive, solid evidence for the proposed relationships. Dai *et al*. [5] developed a way to forecast e-commerce demand. The method aims to extract useful prediction factors from large amounts of data, capturing diverse influences on demand. The algorithm seeks to identify key features from a large set, avoiding the problem of overfitting. The method accurately forecasts e-commerce demand using extensive data validated with a dataset from China's top e-commerce platform.

Wang *et al*. [30] created a way to connect customer needs and product design. The goal is to translate customer needs into specific design details more easily, improving design efficiency. Using a Convolutional Neural Network (CNN), the method maps customers' natural language expressions of their needs to specific product specifications. The technique improves teamwork in product design by aligning customer preferences with practical design details. Gao *et al*. [7] developed a technique to suggest items for social e-commerce. The method combines user-item interaction data from e-commerce apps with social relation data from social media. Their CROSS framework integrated both kinds of data to enhance re-commendation accuracy. The framework stressed the significance of combining user-item interactions and social relations for e-effective recommendations in social e-commerce.

Ma *et al*. [18] proposed the Social Graph Neural Network-based interactive Recommendation (SGNR) scheme framework to refine e-commerce- experience-s. The method improved recommendation accuracy and addressed the- user cold-start issue by leveraging social connections among users. SGNR modeled recommendation as a multi-step decision-making process, actively incorporating user feedback to maximize long-term user benefit. The method boosted e-commerce suggestions, solving accuracy and user cold-start problems. Xu *et al*. [31] introduced a framework for predicting income in stay streaming e-trade. The framework addresses the mission of insufficient sales prediction, which causes stock problems and income loss. The framework integrates awesome capabilities unique to live-streaming e-commerce, including anchor recognition's effect on product income. The proposed framework gives sensible blessings, assisting merchants in accurate sales prediction and effective advertising techniques.

Chang *et al*. [3] proposed an approach for e-commerce marketplace achievement. The approach analyzes the equilibrium of premier mixture techniques, together with channel sales modes and guarantee financing schemes. The method explores how these strategies help absolutely everyone in e-trade, mainly online, along with small enterprise providers, logistics partners, and banks. The approach offers theoretical help for modern monetary practices within the e-commerce enterprise. Liu *et al*. [15] advanced a method for dynamic e-trade recommendations. The technique aims to appropriately represent a person's pursuits over the years, enhancing advice performance. Their Interest Evolution-driven Gated Neighborhood (IEGN) model uses graph neural networks to seize relational statistics in consumer-item interplay graphs. The method emphasizes relational information and temporal dynamics, main to superior advice performance and user delight.

Kim *et al*. [14] created a method for an e-trade platform's delivery service. The method pursues to optimize profit allocation from usage and shipping costs, thinking about a monopolistic e-commerce marketplace and sided marketplace principle. The method entails formulating equations for sellers' and buyers' demand, thinking about move institution externalities. The method assists e-commerce systems in laying out effective pricing techniques for advanced competitiveness and sustainable increase. Liu *et al*. [16] introduced a Time-Preference Gate Network (TPGN) for spotting e-trade buy intentions. TPGN enhances prediction accuracy by considering users' category alternatives and long-term pastimes. The TPGN model complements the Long Short Term Memory (LSTM) architecture by integrating preference gates and two-time *c* programming language gates. TPGN demonstrates progressed accuracy in shooting the complexities of consumer conduct in e-trade settings.

Shen [23] proposed an algorithm for recommending clients primarily based on social relationships. The algorithm aims to decorate guideline accuracy by leveraging social dynamics and refining subject matter function extraction. The progressed K-way rules reduce clustering feature fluctuations, leading to more advantageous recommendation accuracy. The algorithm demonstrates consistent performance, achieving average accuracy from 78.9% to 95.9%. Sales *et al*. [22] proposed multimodal deep neural networks for enhancing e-commerce catalogs. The aim is to robotically structure, update, and overview catalogs by deriving standardized descriptions from unstructured statistics like textual content and images. The approach includes gear to pick out insufficiently descriptive visible and textual statistics for manual development. The approach enhances the seek engine's overall performance and digital shop database employer.

Dhote *et al*. [6] analyzed the world of e-commerce based on the users' customizable shopping experience to avoid high congestion in the network. To resolve this, an Adaboost-based deep learning approach and hybrid geometric sampling were applied to managing the classification task of imbalance data prediction among user requirements. Churn rate prediction applies highly diverse solutions using accuracy, precision, specificity, and sensitivity to meet non-churn users' demands in e-commerce links. The result demonstrated reduced data imbalance and user demand prediction in e-commerce links. Pethuraj *et al*. [20] introduced a contingent resource allocation process for data optimization to improve the quality of service in e-commerce applications. This research applied federated learning to identify stagnancies across multiple demands from user devices and access the requested demand density. The data analysis from existing backlogs accounted for delay prevention, maximized the Quality of Service (QoS), and validated the application response from the user.

An anomaly detection approach based on correlation analysis and K-means clustering was presented by Wang *et al*. [29] for seasonal time-series data. The method uses intra-seasonal correlations and temporal patterns to find anomalous trends. On increasing sensitivity, it dynamically modifies detection thresholds according to correlation coefficients. K-means clustering integration improves anomaly segmentation in seasonal patterns that fluctuate. The suggested technique achieves results ranging from 85.3% to 94.6%, indicating high anomaly identification accuracy. In datasets with sparse time intervals or poor seasonal structure, the model's performance deteriorates, making correlation-based detection ineffective.

A multi-task learning system for intelligent push in e-commerce tailored advertising was presented by Hou *et al*. [10]. By combining the modeling of ad click-through rate estimation with user preference prediction, the system seeks to maximize user engagement. The approach decreases data sparsity problems and increases learning efficiency by sharing representations across tasks. The suggested methodology exhibits engagement uplifts ranging from 7.8% to 15.2% over single-task baselines, dynamically adapting to user behaviors over several sessions. Cold-start users with little past interaction data are difficult for the model to handle, which reduces the effectiveness of personalization in early sessions.

3. Methods

3.1. Data Collection

The proposed method assimilates two data sources presented in Table 1 for sales forecast and product demand. The first data source is generic about product description with its quantity, stock, sales, value, etc., the second dataset forecasts its demand and returns based on value. This demand factor identifies stagnancies and extracts the precise product/ service demands throughout. Using these data sources, the proposed method is constructed as shown in Figure 1.

In this illustration, the products and their services (how to use, warranty, support, etc.,) are extracted from the first data source. The actual demand and demand based on returns are extracted from the data sources 2, for which a fuzzy process is applied. This process is validated for different clustering and de-clustering processes such that actual demand is extracted (Figure 1).

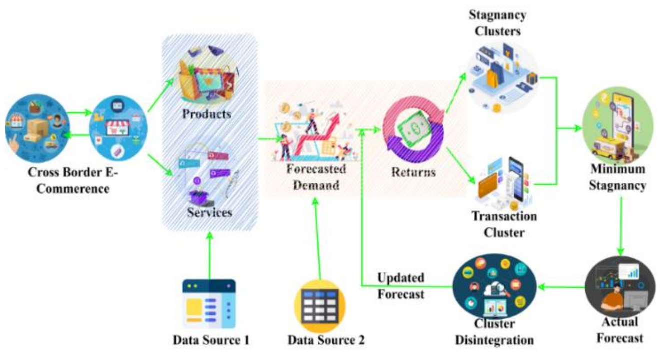


Figure 1. Proposed method using data sources.

3.2. Iterative C-Means Clustering Method for User Demand Prediction

ICCM method is designed to improve the prediction efficacy of user demands based on cross-border e-commerce products/ services inputs. In this analysis, the inputs are obtained from the domestic e-commerce i.e. the cross-border transactions observed in different time intervals. This proposed method aims to reduce the false user demands in analyzing cross-border transactions. The challenging task is forming the clustering method through fuzzy derivatives-the two pairs such as returns, transactions, and returns, stagnancy observed from current cross-border transactions. From this instance, the current cross-border transactions are compared with the previous cross-border transactions to ensure accurate user demand prediction. The previous cross-border transactions observed instances are stored as records for future analysis.

The user demands on products/services are forecasted through fuzzy C-means clustering. Different methods are used to forecast the user demands for reliable transactions. In this observation, the returns based on transactions and goods stagnancy are differentiated using ICCM to identify the user's actual product/service demands. The clustering process is recurrently processed until the transactions in classified the returns with minimum stagnancy that is similar for time and day. The cluster formation using fuzzy derivatives reduces the risk of false user demands. The errors are observed as an instance of misdetection of activity or recognition. First method precision marketing of cross borders, Let $a(t)$ and $b(t)$ denote the sequence of product/service demands and distributions observed from the initial cross border e-commerce scenario such that the forecast on product/service demand $FD(t)$ is given as;

$$FD(t) = a(t) + b(t) - fud \tag{1}$$

Such that,

$$arg\min_{t} \sum fud(t) \forall a(t) + b(t) \tag{2}$$

In the above Equations (1) and (2), the variable *fud* is the false user demand and the objective of reducing the false user demand for all $a(t)+b(t) \in FD(t)$ is defined as identifying the reliable forecasted demand. The return rtn_s is performed based on two segments (i.e.,) transaction (T_s) and goods stagnancy (G_s). The actual return conditions in $rtn_s=T_s+G_s$ such that the goods' stagnancy is detected between the transactions, the variable N represents the number of forecasted demands on products/services in the initial instance. Therefore, the condition $G_s=(N\times rtn_s)-T_s$ is used for addressing current cross-border e-commerce demand that is to be differentiated from the instance to ensure good returns for the e-commerce companies. Therefore, the forecast on different products/services demands analysis is a key factor in improving the transaction rate with stagnancy-less returns.

3.2.1. FCM Clustering Method

The Fuzzy C-Means (FCM) Clustering Method is a soft clustering technique that assigns data points to multiple clusters, reducing the need for hard classification, especially in demand forecasting where customer purchasing patterns overlap.

The FCM algorithm follows these key steps:

- Initialize cluster centers: randomly initialize cluster centroids for C clusters in the feature space.
- Calculate membership values: assign a membership value u_{ij} to each data point x_i for cluster j, based on its distance from the centroid, using Equation (3):

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{3}$$

In Equation (3), m is the fuzzification parameter controlling the level of cluster overlap, and d_{ij} is the Euclidean distance between x_i and the cluster centroid j.

- Update cluster centers: compute new cluster centroids based on membership values Equation (4):

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{4}$$

- Repeat until convergence: iterate steps 2 and 3 until the change in cluster centers falls below a defined threshold ∈.
- Benefits and drawbacks: allowing partial memberships helps manage overlapping clusters. Membership values provide additional data structure information. Often more resilient to outliers than rigid grouping. The significant impact of first cluster center selection on results: The algorithm may converge to local optima. The appropriate number of clusters is difficult to determine.

3.2.2. Integration and Implementation

- Implementation: python's scikit-fuzzy, MATLAB's Fuzzy Logic Toolbox, and R's e1071 can implement FCM.
- Contextual Integration: the FCM method was likely adapted and merged into the proposed ICCM in your work to analyze cross-border e-commerce transactions and user needs.

The Integration and Implementation of the FCM clustering method in precision marketing involves:

- Preprocessing data: cleans and standardizes raw transactional data from e-commerce platforms. Extracts relevant features like purchase frequency, transaction amount, and browsing history.
- Applying FCM for user segmentation: feeds extracted features into the FCM clustering algorithm. Determines optimal number of clusters using techniques like Xie-Beni index or Silhouette Score. Assigns user membership to multiple clusters for probabilistic interpretation of user behavior.
- Model optimization and parameter tuning: fine-tunes fuzzification parameter to control hard and soft clustering. Sets convergence criteria and maximum iteration limits for computational efficiency.
- Integration with precision marketing system: integrates curated user profiles with recommendation systems for personalized marketing strategies. Informs inventory management systems. Establishes a feedback loop for dynamic cluster refinement.

4. Data Analysis

The study uses two main data sources to analyze user demand in cross-border e-commerce transactions. The first source is product descriptions and associated details [12], which includes generic information on product descriptions such as quantity, stock levels, sales figures, value, usage instructions, warranty details, and support services. The second source is product demand and returns forecasting [11], which forecasts product demand and analyzes returns based on value, providing insights into market trends, customer satisfaction, and product performance. The study combines these two datasets to comprehensively analyze product descriptions, associated services, and actual demand data for a more holistic view of product demand. Researchers applied fuzzy processes and various clustering techniques using the ICCM to differentiate between genuine user demand and misleading data, enhancing the accuracy of demand forecasts and providing valuable insights for cross-border e-commerce

4.1. Data Analysis-1

- **Demand and Forecast**

The short data analysis-I is used for statistical assessment of demand forecast, and the (T_s, G_s) under $\underset{t}{arg\,min}$. And $argmax_t \forall FD(t)$. This is statistically represented in Table 2.

The data tabulation presented above is classified based on $argmin_t \forall FD(t)$. This demand detection is varied between 10% and 40% under the $a(t)+b(t)$. In this process, the forecast is carried out based on $G_s=(N\times rtn_s)$. The returns are finalized for different (T_s:G_s) under high differences. As the difference is high, then $T_s>G_s$ and for lesser difference, $T_s<G_s$. The stable demand forecast is observed between successive transactions to ensure a low difference is observed to identify. $T_s=G_s$ (Table 2).

Table 2. Demand, forecast (T_S,G_S).

Condition	Demand	Forecast	Difference	T_s:G_s
$argmin_t$	$FD(t)$ =10%	0.74	±13.2	(0.41:0.31)
	$FD(t)$ =20%	0.72	±6.5	(0.8:0.52)
	$FD(t)$ =30%	0.78	±8.5	(0.65:0.45)
	$FD(t)$ =40%	0.84	±20.1	(0.45:0.81)
$argmax_t$	$FD(t)$ =10%	0.41	±12.3	(0.36:0.92)
	$FD(t)$ =20%	0.52	±2.8	(0.81:0.65)
	$FD(t)$ =30%	0.64	±10.2	(0.52:0.68)
	$FD(t)$ =40%	0.50	±19.2	(0.25:0.87)

- **End of Data Analysis-I**
- **Clustering Process Initialization**

Let $CP(T_s)$ and $CP(G_s)$ represent the cluster formation of $a(t)$ and $b(t)$ observed in different t time intervals, and fud is observed in all G_s such that;

$$CP(T_s) = N * T_s :: a(t) + b(t), \forall\, fud = 0 \tag{5}$$

and,

$$CP(G_s) = \frac{fud}{N} G_s :: fud * a(t) + b(t), \forall\, fud \neq 0 \tag{6}$$

As represented in Equations (5) and (6), the clusters are observed from the instances ($N\times T_s$) and $\left(\frac{fud}{N} \times G_s\right)$ are mapped with $FD(t)$. This paper uses a fuzzy clustering model based on cluster formation to avoid false user demands. The solutions are generated with C-means clusters and C-clustering centers. Now, based on the fuzzy C-means cluster as in Equation (5), equation (6) is rewritten as;

$$FD(t) = \begin{cases} CP(T_s) = N * T_s :: a(t) + b(t), & \forall fud = 0 \\ CP(T_s) - CP(G_s) = N * T_s : a(t) + b(t) - \frac{fud}{N} G_s :: fud * a(t) + b(t), & \forall fud \neq 0 \end{cases} \tag{7}$$

For the above C-means cluster formation based on transactions and goods stagnancy, the sequence of $G_s \in rtn_s$ is to be precomputed on facing the first goods stagnancy as in Equation (5). This is computed to identify the false user demands from actual demand in the cross-border e-commerce platform using the fuzzy clustering model. The differentiating transaction and goods stagnancy with the available dataset is processed using clustering. The clustering representation is presented in Figure 2.

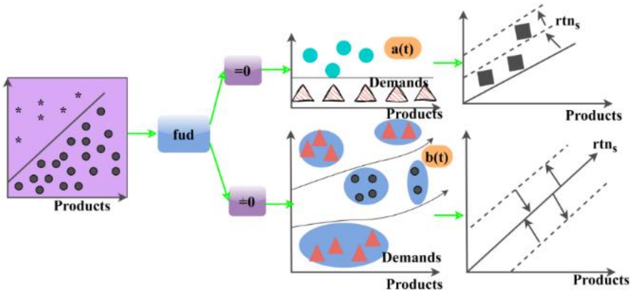


Figure 2. Clustering representation for a(t) and b(t).

The fuzzy clustering process is first assumed for $G_s = T_s$ condition where demand and forecast of products are the same. The clustering process degrades its *fud* based classifications for G_s and T_s such that if $fud=0$ then rtn_s rtn_s increases; the failing case fluctuates irrespective of the demands. The separating condition is the $a(t)$ and $b(t)$ for the clusters where $FD(t)$ relies on $CP(T_s)$ and $CP(G_s)$ consecutively. The initiating condition is the $rtn_s \forall$ all T_s observed if $fud=0$ (Refer to Figure 2).

For this process, the consecutive goods stagnancy detection conditions in $N \in G_s$ is given as;

$$N(G_s) = \left(1 - \frac{G_s}{N}\right) PcT^* + \frac{T_s}{N} \sum_{i=1}^{rtn_s} \frac{\left(1 - \frac{T_s}{N}\right)^{i-1} G_{s-I}}{T} \tag{8}$$

In Equation (9), the sequence of previous cross-border transactions is indicated as PcT^*. Therefore, based on the above sequence, $B(t)=CP(T_s)-CP(G_s)[1-N(G_s)]$ is the last output for $fud \neq 0$ condition. The degree of stagnancy (θ_{Ts}) and (θ_{Gs}) for transactions and goods in the initial stage is given as;

$$\theta_{T_s} \approx \frac{CP(T_s).T}{\sum_{i \in t} [N(G_s) + a(t) + b(t)]_i} \tag{9}$$

and,

$$\theta_{G_s} \approx \frac{CP(T_s).T + CP(G_s).T}{\sum_{i \in t} \left[(N \cdot T_s)_{i\left(1 - N(G_s) \cdot CP(T_s)\right)} \right]_i} \tag{10}$$

The Equations (9) and (10) are used to compute the degree of stagnancy for the formed clusters based on transactions and goods. For instance, the stagnancy clusters *Scs* and transaction clusters *Tsc* are differentiated and stored from the previous cross-border transactions for future processes. In this initial clustering process, the computation of θ_{Ts}, θ_{Gs}, $CP(T_s)$ and $CP(G_s)$ are the serving inputs for the actual demand identification across borders. The clustering processes are iterated until the transactions in differentiating the forecasted demands help to identify the actual demands and false user demands in the cross borders between T_s and $G_s \in t$.

4.2. Data Analysis-2

- **Degree of Stagnancy**

Based on the Table 2 $FD(t)$, the degree of stagnancy for the cases in Equations (9) and (10) are validated in Table 3.

The stagnancies under θ_{Ts} and θ_{Gs} are estimated for direct and indirect $FD(t)$ ratios. Considering the $N(G_s)$ as the combination of θ_{Ts} and θ_{Gs} the $fud \neq 0$ condition is planned to be thwarted. The $fud \neq 0$ differentiates rtn_s until $T_s = G_s$ is balanced. The maximum value (=1) represents the maximum false forecast and no returns, as illustrated in Table 3 below. Using the $a(t)$ and $b(t)$ independently identifies the stagnancies in any cross-border sale. The transactions are optimal in defining multiple forecasts for the products and demands. Therefore, the highest value observed instances are to be extracted using demand differentiations. This clustering process is discussed in the following section.

Table 3. Degree of stagnancy analysis based on Equations (9) and (10).

		FD(t)=10%	**FD(t)=20%**	**FD(t)=30%**	**FD(t)=40%**	θ_{Ts}	θ_{Gs}
a(t)	FD(t)=10%	1	0.35	0.41	0.45	0.85	0.05
	FD(t)=20%	0.45	1	0.65	0.71	0.72	0.09
	FD(t)=30%	0.52	0.65	1	0.75	0.78	0.26
	FD(t)=40%	0.49	0.75	0.93	1	0.65	0.39
b(t)	FD(t)=10%	0.52	0.45	0.32	1	0.4	0.8
	FD(t)=20%	0.75	0.52	1	0.42	0.58	0.76
	FD(t)=30%	0.89	1	0.81	0.73	0.63	0.62
	FD(t)=40%	1	0.93	0.85	0.75	0.7	0.58

- **End of Data Analysis-2**

- **Clustering Process for Differentiating the Demands**

In the demand differentiating process, the fuzzy clustering model is used for identifying the actual demands of θ_{Ts} or θ_{Gs} and validating *fud*. As this cluster formation relies on previous cross-border transactions based on $a(t)$ and $b(t)$, the more reliable precision marketing of cross-border e-commerce is achievable using the clustering process. The clusters are formed using fuzzy derivatives on two pairs, i.e., returns, transaction, and returns, stagnancy. The number of product/ service demands may vary, throughout the previous cross-border transactions helps to classify the two pairs for defacing the returns for identifying the actual demand. In particular, this model performs two types of processing, namely transaction differentiation and actual demand identification. In the transaction differentiation process, Ts and Gs Are identified to improve the stored previous cross-border transactions of $a(t)$ and $b(t)$. Instead, in the demand identification, different instances of goods stagnancy are identified to improve profits and better assess and detect false user demands. The validation of $a(t)+b(t)\in rtn_s$ is clustered under T_s and G_s based on identifying the minimum degree of stagnancy occurrence. In the clustering process $a(t)$ and $b(t)$ observed in the different instances is classified alone based on the minimum degree of stagnancy. The minimum degree of stagnancy is identified from $N(G_s)$ and (Nt) throughout, after which the Iterative C-means Clustering (ICC) model is used to update the actual returns for providing precise user demands. The sequential cluster formation using fuzzy derivatives ($C_{form}(\vartheta)_1$ *to* $C_{form}(\vartheta)t$) is computed as;

$$\left.\begin{aligned} C_{form}(\vartheta)_1 &= t_{s_1} \\ C_{form}(\vartheta)_2 &= 2T_{s_2} - 2(G_s)_2 - CP(Tcs+Scs)_1 \\ C_{form}(\vartheta)_3 &= 3T_{s3} - 3(G_s)_3 - CP(Tcs+Scs)_3 \\ &\vdots \\ C_{form}(\vartheta)_t &= N * T_{s_t} - N(G_s)_t - CP(Tcs+Scs)_{t-1} \end{aligned}\right\} \quad (11)$$

In Equation (7), ensure that $CP(T_{cs}+S_{cs})$ terms are consistently indexed across all equations. If N represents a general variable, clarify whether it is a constant or a function. If the cluster formation process involves weighted fuzzy derivatives, explicitly define how G_s and T_s are computed.

$$\left.\begin{aligned} U(\alpha(rtn_s))_1 &= G_{s_1} \\ U(\alpha(rtn_s))_2 &= 2\left(G_{s_2}\right) + FD(1) \\ U(\alpha(rtn_s))_3 &= 3\left(G_{s_3}\right) + FD(3) \\ &\vdots \\ U(\alpha(rtn_s))_t &= N\left(G_{s_t}\right) + FD(t-1) \end{aligned}\right\} \quad (12)$$

In Equation (8), ensure that $FD(t\text{-}1)$ is well-defined in the preceding text. If G_s is a cumulative function or derivative, clarify whether it is normalized or scaled. Consistently index FD terms across equations.

The process of minimum stagnancy pairs generates actual forecasts from $C_{form}(\vartheta)_1$ to $C_{form}(\vartheta)t$ sequences, and updates the sequence of the actual returns ($U(\alpha(rtn_s))_1$ to $U(\alpha(rtn_s))_t$). Now, clustering is iteratively performed using fuzzy derivatives based on the user demand for the products/ services observed in the sequences. The condition of $rtn_s\in C_{form}(\vartheta)$ must not be equal to $rtn_s\in U(\alpha(rtn_s))$ is the appropriate clustering condition. If the occurrence of goods stagnancy is detected in the first sequence, then the update of actual returns is performed using current cross-border transactions; this means, the transactions that are differentiated as per the norms of goods stagnancy presence, then $N(G_{st})+FD(t\text{-}1)$ is the returns updating sequence. In the clustering process, the initial set is differentiated from the demand that defaces the returns using fuzzy derivatives. In such pairs, the matching of $C_{form}(\vartheta)t$ and $U(\alpha(rtn_s))$ is verified such that $T_s=\{Ts\cup CP(T_s)\}$ and $Gs=\{C_{form}(\vartheta)_t\cap CP(G_s)\}$ is clustered alone to provide precise user demands. The update of the actual returns is achieved at its first level from which the minimum stagnancy pairs are alone extracted. After the clustering process, the product/ service demand forecast in the current transaction is compared with previous cross-border transactions based on the sequence of good returns observed. Here, the inputs of $CP(G_s)$ and G_s used to update the previous cross-border transactions using the training set for all the classified forecasted demands under goods stagnancy. If the false user demands are identified in any instance, the new sequence of transactions is further distinguished and clustered under fuzzy derivatives, where $rtn_s\in Ts$ is satisfied. Based on the C-means clustering model, the condition $Tcs>Scs$ output as "1", whereas the condition $Tsc<Scs$ output as "0" for improving benefit to the e-commerce companies. If zero is observed in any transaction, then the false user demand forecast is detected from the sequence, and hence, the demand forecast of any $T_s$inG_s initiates the sequential cluster formation and updating returns as in Equations (7) and (8). Now, the good returns are required to be verified by the fuzzy C-means clustering process and updates from the previous cross-border transactions. The clustering decision flow is graphically given in Figure 3.

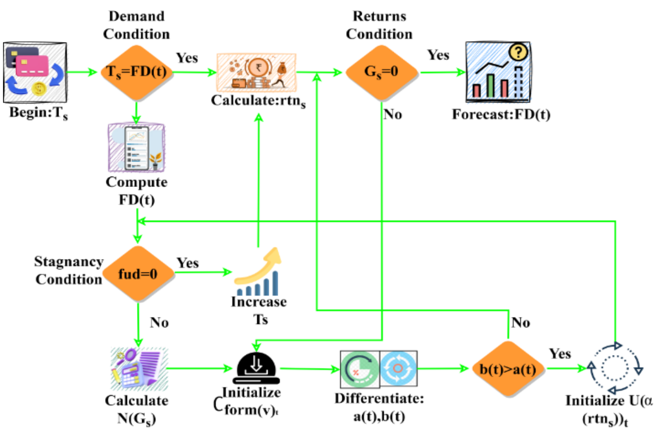


Figure 3. Graphical representation of clustering decision flow.

The clustering decision flow is graphically presented in above Figure 3. The demand, returns, stagnancy, and clustering conditions are used in the decision process to identify rtn_s based transactions. If the $Tsc<Scs$ is the satisfying condition, then stock-based transactions with fluctuations are analyzed. Using the different block conditions, $C_{form(v)t}$ and $U(\alpha(rtn_s))_t$ are differentiated. Considerably the clustering condition fits beyond $Tcs>G_s$ and $T_s=G_s$ conditions to increase the performance of demand forecasting. However, the $fud=0$ and $fud\neq 0$ cases are distinguished earlier to ensure Tcs and Scs ranges. The clustering process of two pairs occurring in sequence in the proposed model is to ensure profits for the e-commerce company. In this computation, initially, the identified actual demand is used to differentiate the demand based on forecasted products/ services. In the computation process, the training set serves as the input for similarity analysis with the extraction of minimum stagnancy pairs obtained to forecast the user demands. In the previous transactions retrieval, the minimum stagnancy pairs are fetched to ensure the goodwill of the products/ services to verify if there is any goods stagnancy. If minimum stagnancy occurs in any transactions, then the actual forecast is performed. Instead, of the maximum stagnancy occurrence in any transactions, the actual returns are updated to improve precise user demands. Here, the cluster formation-based fuzzy derivatives and updated returns differ from the necessary product/ service demand forecast.

Equations (13) and (14) show the occurrence of stagnancy and transaction clusters at different times. If the minimum stagnancy satisfies the first pair instead of the maximum stagnancy satisfies the second pair to ensure good returns of the products/services, the forecast is updated for the increasing user demand. Hence, this is not considered in the clustering process and is iterated until the end of transactions.

$$\left.\begin{array}{c} \mathrm{C}_{form}(\vartheta)_1 = G_{s_1} \\ \mathrm{C}_{form}(\vartheta)_2 = 2G_{s_2} + CP(G_s)_1 + fud_1 \\ \mathrm{C}_{form}(\vartheta)_3 = 3G_{s_3} + CP(G_s)_2 + fud_3 \\ \vdots \\ \mathrm{C}_{form}(\vartheta)_t = NG_{s_t} + CP(G_s)_{t-1} + fud_{t-1} \end{array}\right\}, stagnancy\ cluster\ based\ occurrence \quad (13)$$

and,

$$\left.\begin{array}{c} \mathrm{C}_{form}(\vartheta)_1 = 0 \\ \mathrm{C}_{form}(\vartheta)_2 = CP(T_s)_1 + 2T_{s_1} - fud_1 \\ \mathrm{C}_{form}(\vartheta)_3 = CP(T_s)_2 + 3T_{s_2} - fud_2 \\ \vdots \\ \mathrm{C}_{form}(\vartheta)_t = CP(T_s)_{t-1} + NT_{s_t} - fud_t \end{array}\right\}, transaction\ cluster\ based\ occurrence \quad (14)$$

4.3. Data Analysis-3

- **Clustering Outcomes for Stagnancies and Transactions**

The clustering outcomes for stagnancies and transactions are tabulated below.

Table 4. Clustering outcomes for stagnancies and transactions.

Conditions	Category	$\mathrm{C}_{form}(\vartheta)t$ (Stagnancy)	$\mathrm{C}_{form}(\vartheta)t$ (Transaction)	$U(a(rtn_s))_t$	*fud*
$T_s>G_s$	Electronics	0.03	0.031	0.21	0.154
	Consumables	0.058	0.048	0.25	0.145
	Decors	0.101	0.105	0.28	0.32
	Clothing	0.13	0.118	0.24	0.214
$Ts=G_s$	Electronics	0.07	0.03	0.32	0.314
	Consumables	0.108	0.089	0.38	0.189
	Decors	0.132	0.105	0.41	0.324
	Clothing	0.16	0.132	0.42	0.306
$T_s<G_s$	Electronics	0.14	0.121	0.45	0.348
	Consumables	0.162	0.101	0.48	0.364
	Decors	0.21	0.09	0.42	0.297
	Clothing	0.184	0.085	0.51	0.369

The data analysis in Table 4 concerns the product type as electronics, consumables, decors, and clothing. The demands and fud are analyzed for the clustering rates for the 4 categories independently. This is analyzed and $T_s>G_s$, $Ts=G_s$, and $T_s<G_s$ criteria as presented. The first criterion is satisfying based on the condition $b(t)>a(t)$ to reduce *fud*, whereas the switchover occurs from $Ts=G_s$ and then moves to $T_s>G_s$ Conditions. Such conditions are thwarted using $U(a(rtn_s))_t$ with its accommodation between $FD(t)$ and $FD(t\text{-}1)$. These intervals are defined under multiple t to distinguish stagnancy and transaction clusters.

- **End of Data Analysis-3**

In both the processing, the false user demand is augmented before the forecast demand is updated as;

$$U(FD(t)) = \begin{cases} U(FD(t))_1 = \dfrac{1\left(G_{s_1}\right) + T_{s-1}}{PcT^*} \\ U(FD(t))_2 = \dfrac{2\left(G_{s_2}\right) + T_{s-2}}{PcT^*} - fud_1 \\ U(FD(t))_3 = \dfrac{3\left(G_{s_3}\right) + T_{s-3}}{PcT^*} - fud_2 \\ \vdots \\ U(FD(t))_t = \dfrac{N\left(G_{s_t}\right) + T_{s-t}}{PcT^*} - fud_t \end{cases} \quad (15)$$

The forecast demand is updated at the end of all the transactions or before the start of the next transaction. In the forecast, the update is performed along with updated returns and transactions, providing accurate user demands. Therefore, the other derivative clusters are disintegrated, where the first pair represents the forecast update for all the T_s and later represents the goods' stagnancy. It is to be addressed that either the stagnancy or transaction clusters i.e. clustered under T_s or G_s in the cross borders. From the previous cross-border transactions, the training set with inputs G_s, θ_{Ts} and *fud* is used for the next cluster formation. Using the fuzzy derivative groups are disintegrated after the complete transaction. In this case, the false user demands is computed as follows:

$$fud = \frac{N * rtn_s - CP(T_s) * \left(\theta_{T_s}\right) + t}{CP(G_s).t} \quad (16)$$

such that,

$$Z_{rtn_s} = N * T_s = \theta_{T_s}.CP(T_s) + \mathrm{C}_{form}(\vartheta)_t - a(t) + b(t) \quad (17)$$

Equations (16) and (17), the occurrence of differentiation of the demand that defaces the returns is classified based on minimum stagnancy. This false user demand is used to validate the next sequential assessment with the probability of clustering in either transaction clusters or stagnancy clusters. Instead, if fud=0, then the next computation sequence of $CP(T_s)$=*true*, is grouped under transactions. Similarly, if $Tcs>Scs$, then fud=0 is to improve the transaction rate. Therefore, the update of the forecast means the prediction efficacy is improved. The other derivative clusters are disintegrated until the above condition fails. Instead, the occurrence of a minimum degree of stagnancy continuously ensures the goodwill of the products/ services until it extracts the cross-border transaction for false user demand forecasts. Hence, the unnecessary demands are reduced, thereby improving prediction efficacy.

4.4. Data Analysis-4

- **Updated Forecast and Minimum Stagnancy**

Table 5 presents the minimum stagnancy observed from *FD*(t) variances. This is observed from the (t-1) clustering *Ts* to enhance the actual forecast.

Table 5. Minimum stagnancy from *FD*(t) variances.

Category	*FD*(t) (%)	Minimum Stagnancy	*FD(t-1)* Difference	Updated Forecast
Electronics	10	0.13	±0.15	0.84
Consumables		0.08	±0.08	0.76
Decors		0.12	±0.121	0.72
Clothing		0.107	±0.098	0.65
Electronics	20	0.19	±148	0.68
Consumables		0.14	±0.07	0.41
Decors		0.17	±0.128	0.52
Clothing		0.15	±0.102	0.65
Electronics	30	0.24	±145	0.68
Consumables		0.18	±0.09	0.041
Decors		0.22	±0.124	0.65
Clothing		0.23	±0.108	0.115
Electronics	40	0.37	±145	0.21
Consumables		0.21	±0.085	0.052
Decors		0.35	±0.135	0.81
Clothing		0.28	±0.115	0.75

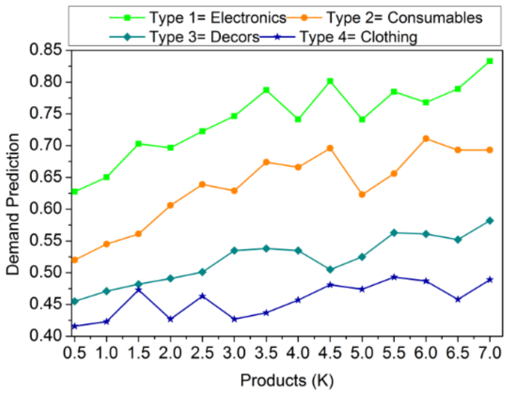
Table 5 presents the minimum stagnancy observed from *FD*(T) variances. This is observed from the (*t-1*) clustering T_s to enhance the actual forecast. Therefore, the actual forecast is *FD*(t)±*fud* observed during the clustering process, specifically the difference between t and (t-1)th an instance is the variables that ensure $a(t)>b(t)$ condition. Therefore, the updated forecast is the more precise outcome of the information provided in data source 2 after cluster disintegration. Therefore, the consecutive assessment of T_s and G_s for rtn_s Identified the precise variance in minimum stagnancies (Table 5).

- **End of Data Analysis-4**

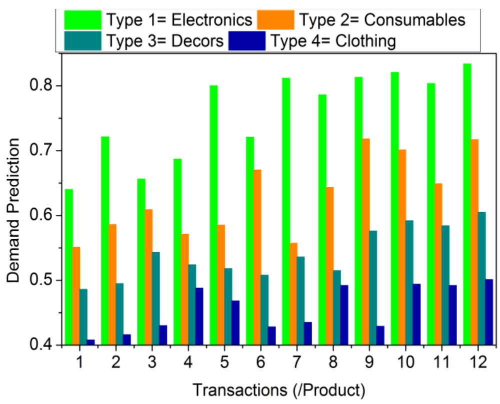
5. Discussion

The discussion section concerns the impact of demand prediction, return detection, false demands, differentiation time, and stagnancy detection over electronics, consumables, decors, and clothing. The number of products ranges from 0.5K to 7K and the transaction varies from 1 to 12 per product.

The minimum/maximum false user demands in domestic e-commerce platforms at the time of electronic item transactions are identified to reduce stagnancy. During electronics transactions, false demands are high, reducing good returns for the cross-border e-commerce company. To overcome this issue, the ICCM is designed to improve the product/service demand prediction through different methods. This proposed method enhances the electronic transaction rate with stagnancy-less returns. The minimum degree of stagnancy identified in any electronics transaction between the cross-border e-commerce platform increases false demands. However, false demand identification is performed by fuzzy clustering to predict accurate user demands in the precision marketing of the e-commerce platform. High false demands are detected during electronic transactions, and transactions and goods stagnate. Using the clustering process, the returns based on transaction and goods stagnancy are differentiated to find the actual demand in the e-commerce platform, thereby reducing the unnecessary demand prediction. For instance, if the maximum false demand identified in any electronic transactions is to increase goods stagnancy. The clustering process is iterated until the transactions differentiate the returns such that the high-demand prediction is achieved (Figure 4).



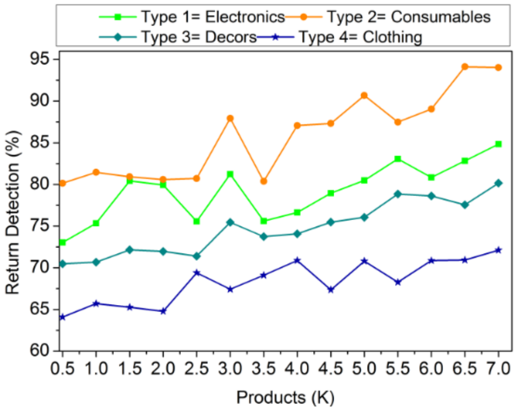
a) Prediction by category.



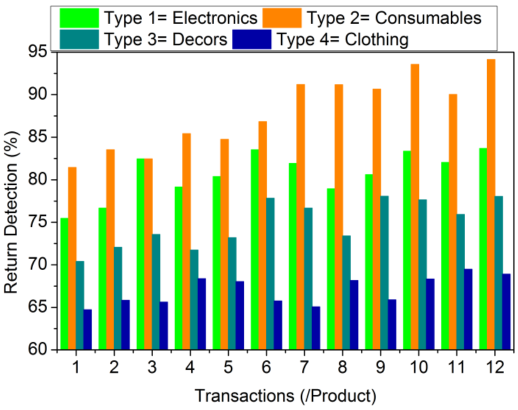
b) Prediction by transactions.

Figure 4. Representation of demand prediction.

In consumables transactions, high stagnancy is addressed with high material composition verification under both classifications. The fuzzy derivatives reduce the transaction and goods stagnancy in domestic e-commerce transactions. For instance, initially, the consumables weights are computed, and then stagnancy is identified to ensure good returns for the cross-border e-commerce companies. The ICCM is applied to identify the minimum degree of stagnancy in consumables transactions that better differentiates two pairs for distinguishing the false demands. If the product/ service demands for consumables differ the clustering process is performed to ensure the goodwill of the products/ services. Such an identified process fails the cross-border transaction for false demand forecasts from which the good returns are achieved. The clustering process is iterated by separating the transaction and goods stagnancy based on returns for identifying the actual user demand. Hence, the consumables are verified and then transacted to the appropriate location. Therefore, the high return detection is satisfied to reduce stagnancy in consumables transactions (Figure 5).



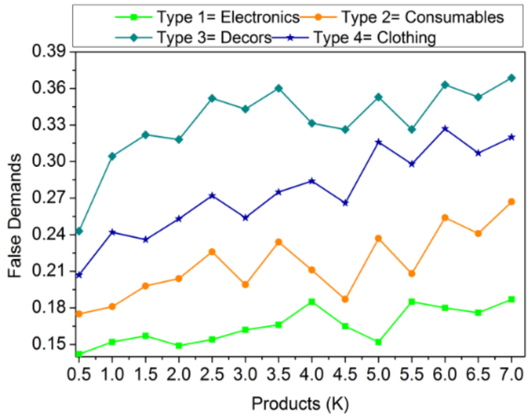
a) Return vs. products.



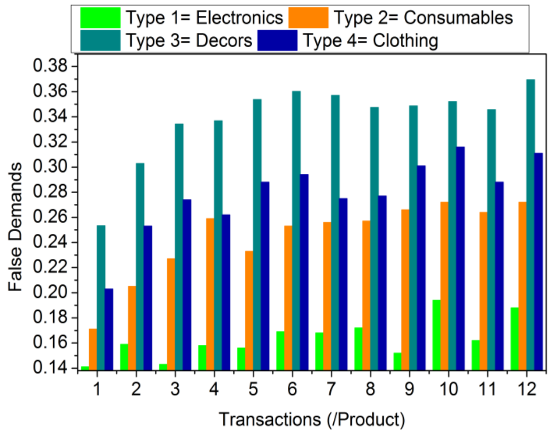
b) Return vs. transactions.

Figure 5. Representation of return detection.

In the domestic e-commerce platform, the decors transaction is performed using ICCM with stagnancy-less returns for false demand forecast. By reducing the transaction and goods stagnancy that increases the actual demand of the decors in the cross border e-commerce transactions. Hence, the décor business must not restrict itself to just decorating the home to avoid such problems. The decors transaction is the profitable business, where, the earnings are higher than investments. Factors that affect the transaction rate are poor product quality, item dissatisfaction, defective items, and incorrect sizing. Based on the fuzzy-based derivative groups, the optimal decors transaction is performed with its minimum degree of stagnancy to satisfy high return detection. For example, based on the user demands, the decors are arranged and packed for transaction to the corresponding user. If the user returns the products, then the clustering process is performed. In this transaction, the stagnancy returns and then returns transactions are clustered independently for identifying the actual demand and then providing precise user demand. Based on the fuzzy derivatives, the return detection is increased with cluster formation (Figure 6).



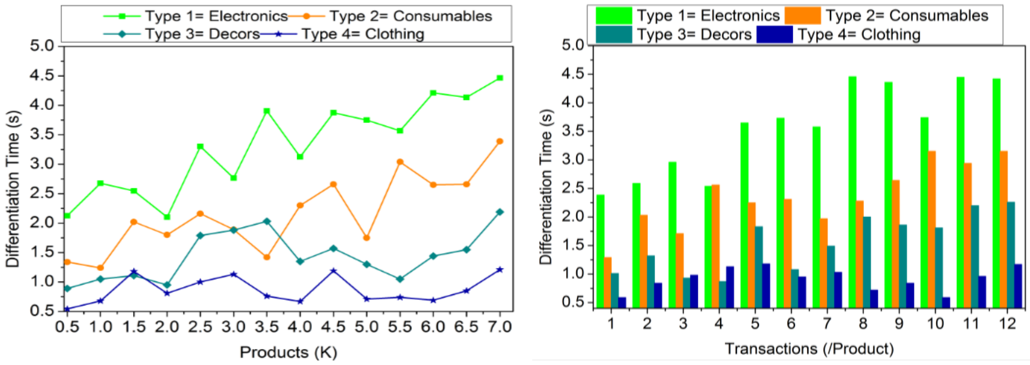
a) False demands vs. products.



b) False demands vs. transactions.

Figure 6. Representation of false demands.

In clothing transactions, ICCM is used to provide high recommendations for identifying the user demands for maximum stagnancy-less returns. The minimum degree of stagnancy is identified in any transaction where products/services are analyzed and then appropriate services to the users. The clustering process is used to show both transaction and goods stagnancy returns using fuzzy derivatives for improving the prediction efficacy. Further, demand differentiation is performed to classify the returns to increase clothing transactions. The stagnancy identified returns retards the cross-border e-commerce transaction such that the clustering process is iterated to identify the actual demand for making better decisions to transact clothing between cross-border. In different user demands observation for clothing, the returns based on poor product quality, false product, size variation, etc. are optimal in identifying stagnancy and then using an updated forecast for the next transaction. Therefore, the nearest possibility of a minimum degree of stagnancy is detected to identify the accurate user demands for clothing. The optimal fuzzy derivative is used to increase the clothing transaction between cross borders. From the instance, the clothing demands are forecasted with high stagnancy detection (Figure 7).

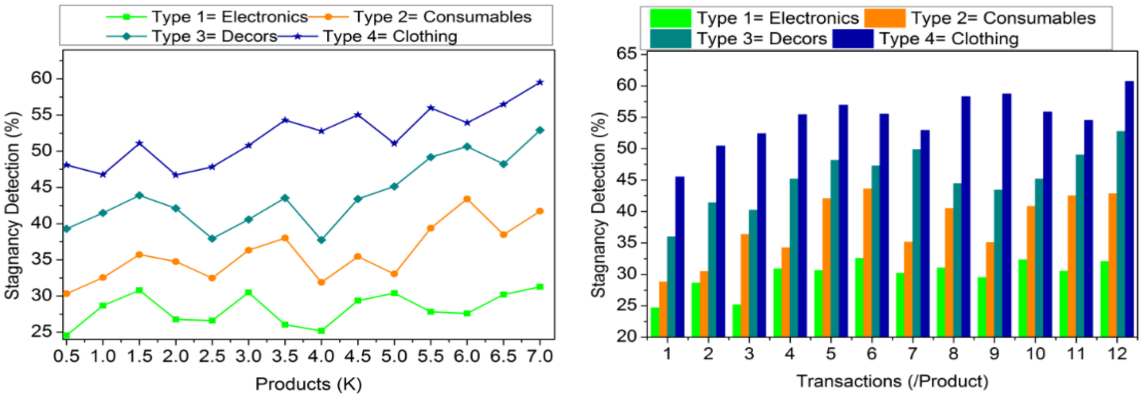


a) Time vs. products.

b) Time vs. transactions.

Figure 7. Representation of differentiation time.

In electronics, clothing, consumables, and decor transactions, the products/services demand-based maximum stagnancy identification is difficult in improving the transaction rate in domestic e-commerce transactions. The appropriate fuzzy-means clustering is generated with maximum prediction efficacy and less stagnancy detection to increase the goodwill of the products/ services. The transaction and stagnancy clusters are identified and segregated through a fuzzy C-means clustering process for identifying the actual demand. Using the transaction and goods stagnancy differentiation, the products/service demands that deface the returns are classified under the minimum degree of stagnancy detection. For predicting the accurate user demands in precision marketing of cross-border e-commerce products/services are forecasted through a fuzzy clustering model. Comparing the product/ service distribution with the previous database for disintegrating the fuzzy-based derivative groups after the transaction is to improve the prediction efficacy of user demands with less stagnancy detection (Figure 8).



a) Stagnancy vs. products.

b) Stagnancy vs. transactions.

Figure 8. Representation of stagnancy detection.

The evaluation parameters for demand forecasting, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Accuracy (Acc), and Coefficient of Determination (R^2), are presented in Table 6. The observed results show varying trends across different models, with R^2 values indicating higher predictive reliability for Model A, whereas RMSE and MAE values highlight the errors associated with each forecast.

Table 6. Comparison off FCM framework with competing algorithms.

Parameter	FCM method	Two-stage feature selection [5]	SGNR [18]	TPGN [16]
Prediction accuracy (%)	90.5	88	86	87
Recommendation precision (%)	92.3	89	91	90
User satisfaction (%)	85.7	80	83	82
Computational efficiency (ms)	150	200	180	170
Scalability	High	Medium	Medium	Medium

6. Conclusions

Cross-border e-commerce transactions are influenced by true and false product/service demands over the years. To improve the complementary return-based transaction, the false demand predictions are to be refrained. The iterative C-means clustering method introduced in this article was optimal to strengthen this improvement. This clustering was performed based on stagnancy and transactions performed to identify minimal distortions. Those identified transactions are differentiated to identify and reduce false demands. Based on the returns the minimal and maximum stagnancies are further derived from the fuzzy process and are grouped. As the minimum stagnancy is observed under the various goodwill returns, the clustering process is disintegrated. This process is iterated under high repetitions to improve successful transactions. Based on the derivative groups the transaction completeness and grouping processes are planned for further improvements.

References

[1] Al-Adwan A., Al-Debei M., and Dwivedi Y., "E-Commerce in High Uncertainty Avoidance Cultures: The Driving Forces of Repurchase and Word-of-Mouth Intentions," *Technology in Society*, vol. 71, pp. 102083, 2022. https://doi.org/10.1016/j.techsoc.2022.102083

[2] Ali-Fakulti M. and Jamil J., "Exploring Pattern Mining with FCM Algorithm for Predicting Female Athlete Behaviour in Sports Analytics," *PatternIQ Mining*, vol. 1, no. 1, pp. 45-56, 2024. https://doi.org/10.70023/piqm245

[3] Chang S., Li A., Wang X., and Zhang J., "Optimal Combination of Platform Channel Contract and Guarantee Financing Strategy in E-Commerce Market," *Transportation Research Part E: Logistics and Transportation Review*, vol. 172, pp. 103094, 2023. https://doi.org/10.1016/j.tre.2023.103094

[4] Chiha A., Vannieuwenborg F., Denis B., Colle D., and Verbrugge S., "Cooperative, Connected and Automated Mobility (CCAM) Services Provisioning in Cross-Border Settings: Techno-Economic Analysis in the Light of Technical Challenges," *Transport Policy*, vol. 140, pp. 68-84, 2023. https://doi.org/10.1016/j.tranpol.2023.06.005

[5] Dai H., Xiao Q., Yan N., Xu X., and Tong T., "Item-Level Forecasting for E-Commerce Demand with High-Dimensional Data Using a Two-Stage Feature Selection Algorithm," *Journal of Systems Science and Systems Engineering*, vol. 31, no. 2, pp. 247-264, 2022. https://doi.org/10.1007/s11518-022-5520-1

[6] Dhote S., Vichoray C., Pais R., Baskar S., and Shakeel P., "Hybrid Geometric Sampling and Adaboost Based Deep Learning Approach for Data Imbalance in E-Commerce," *Electronic Commerce Research*, vol. 20, no. 2, pp. 259-274, 2020. https://doi.org/10.1007/s10660-019-09383-2

[7] Gao C., Lin T., Li N., Jin D., and Li Y., "Cross-Platform Item Recommendation for Online Social E-Commerce," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 2, pp. 1351-1364, 2021. DOI:10.1109/TKDE.2021.3098702

[8] Haddara M., Salazar A., and Langseth M., "Exploring the Impact of GDPR on Big Data Analytics Operations in the E-Commerce Industry," *Procedia Computer Science*, vol. 219, pp. 767-777, 2023. https://doi.org/10.1016/j.procs.2023.01.350

[9] He X. and Liu Y., "Knowledge Evolutionary Process of Artificial Intelligence in E-Commerce: Main Path Analysis and Science Mapping Analysis," *Expert Systems with Applications*, vol. 238, pp. 121801, 2024. https://doi.org/10.1016/j.eswa.2023.121801

[10] Hou M., Zhang M., and Zhang Y., "Application Analysis of Multi-Task Learning Algorithm in E-Commerce Personalized Advertising Intelligent Push," *The International Arab Journal of Information Technology*, vol. 22, no. 2, pp. 303-315, 2025. https://doi.org/10.34028/iajit/22/2/8

[11] Kaggle, https://www.kaggle.com/code/allunia/e-commerce-sales-forecast/input?select=data.csv, Last Visited, 2024.

[12] Kaggle,https://www.kaggle.com/datasets/felixzhao/productdemandforecasting/data, Last Visited, 2024.

[13] Ke J., Wang Y., Fan M., Chen X., Zhang W., and Gou J., "Discovering E-Commerce User Groups from Online Comments: An Emotional Correlation Analysis-Based Clustering Method," *Computers and Electrical Engineering*, vol. 113, pp. 109035, 2024. https://doi.org/10.1016/j.compeleceng.2023.109035

[14] Kim G., Wang W., and Ha H., "Pricing Strategy for own Shipping Service of E-Commerce Platform Using Two-Sided Market Theory," *Electronic Commerce Research and Applications*, vol. 49, pp. 101088, 2021. https://doi.org/10.1016/j.elerap.2021.101088

[15] Liu D., Li J., Wu J., Du B., Chang J., and Li X., "Interest Evolution-Driven Gated Neighborhood Aggregation Representation for Dynamic Recommendation in E-Commerce," *Information Processing and Management*, vol. 59, no. 4, pp. 102982, 2022. https://doi.org/10.1016/j.ipm.2022.102982

[16] Liu Y., Tian Y., Xu Y., Zhao S., Huang Y., Fan Y., Duan F., and Guo P., "TPGN: A Time-Preference Gate Network for E-Commerce Purchase Intention Recognition," *Knowledge-Based Systems*, vol. 220, pp. 106920, 2021. https://doi.org/10.1016/j.knosys.2021.106920

[17] Luo L., Ma X., and Wang Z., "The Moderate-Reputation Trap: Evidence from a Chinese Cross-Border Business-To-Business E-Commerce Portal," *Asia Pacific Journal of Management*, vol. 39, no. 2, pp. 395-432, 2020. DOI:10.1007/s10490-020-09730-0

[18] Ma D., Wang Y., Ma J., and Jin Q., "SGNR: A Social Graph Neural Network based Interactive Recommendation Scheme for E-Commerce," *Tsinghua Science and Technology*, vol. 28, no. 4, pp. 786-798, 2023. DOI:10.26599/TST.2022.9010050

[19] Pandit A., Jalal A., Toma A., and Nachev P., "Analyzing Historical and Future Acute Neurosurgical Demand Using an AI-Enabled Predictive Dashboard," *Scientific Reports*, vol. 12, no. 1, pp. 1-12, 2022. https://doi.org/10.1038/s41598-022-11607-9

[20] Pethuraj M., Bin Mohd Aboobaider B., and Salahuddin L., "Analyzing QoS Factor in 5G Communication Using Optimized Data Communication Techniques for E-Commerce Applications," *Optik*, vol. 272, pp. 170333, 2023. https://doi.org/10.1016/j.ijleo.2022.170333

[21] Rodrigues V., Policarpo L., Da Silveira D., Da Rosa Righi R., and et al., "Fraud Detection and Prevention in E-Commerce: A Systematic Literature Review," *Electronic Commerce Research and Applications*, vol. 56, pp. 101207, 2022. https://doi.org/10.1016/j.elerap.2022.101207

[22] Sales L., Pereira A., Vieira T., and De Barros Costa E., "Multimodal Deep Neural Networks for Attribute Prediction and Applications to E-Commerce Catalogs Enhancement," *Multimedia Tools and Applications*, vol. 80, no. 17, pp. 25851-25873, 2021. https://doi.org/10.1007/s11042-021-10885-1

[23] Shen X., "E-Commerce User Recommendation Algorithm Based on Social Relationship Characteristics and Improved K-Means Algorithm," *International Journal of Computational Intelligence Systems*, vol. 16, no. 1, pp. 1-14, 2023. https://doi.org/10.1007/s44196-023-00321-7

[24] Si D., Li H., Hu D., and Li X., "The Uncertainty of RMB Exchange Rate Expectation and Foreign Investment: Evidence from Cross-Border M and as in China," *Pacific-Basin Finance Journal*, vol. 83, pp. 102213, 2024. https://doi.org/10.1016/j.pacfin.2023.102213

[25] Sreenivasa B. and Nirmala C., "Hybrid Time Centric Recommendation Model for E-Commerce Applications Using Behavioral Traits of User," *Information Technology and Management*, vol. 24, no. 2, pp. 133-146, 2023. https://doi.org/10.1007/s10799-022-00358-8

[26] Sun J., Ge N., Chen X., Feng W., and Lu J., "Truthful Transaction Protocol for E-Commerce Networks Based on Double Auction," *IEEE Transactions on Network Science and Engineering*, vol. 10, no. 2, pp. 709-722, 2022. DOI:10.1109/TNSE.2022.3218642

[27] Tsai P. and Tang J., "Consumers' Switching Intention Towards E-Commerce Platforms' Store-to-Store Pickup Services: The Application of the Extended PPM Model," *Journal of Retailing and Consumer Services*, vol. 75, pp. 103535, 2023. https://doi.org/10.1016/j.jretconser.2023.103535

[28] Wang L., "Establishing Enterprise Information Management Platform Using Cloud Storage Technology Under E-Commerce Environment," *Soft Computing*, vol. 28, no. 4, pp. 3649-3665, 2024. https://doi.org/10.1007/s00500-024-09635-w

[29] Wang X., Yang Y., Ding X., and Zhao Y., "Based on Correlation Analysis and K-Means: An Anomaly Detection Algorithm for Seasonal Time-Series Data," *The International Arab Journal of Information Technology*, vol. 21, no. 6, pp. 978-986, 2024. https://doi.org/10.34028/iajit/21/6/2

[30] Wang Y., Luo L., and Liu H., "Bridging the Semantic Gap between Customer Needs and Design Specifications Using User-Generated Content," *IEEE Transactions on Engineering Management*, vol. 69, no. 4, pp. 1622-1634, 2020. DOI:10.1109/TEM.2020.3021698

[31] Xu W., Cao Y., and Chen R., "A Multimodal Analytics Framework for Product Sales Prediction with the Reputation of Anchors in Live Streaming E-Commerce," *Decision Support Systems*, vol. 177, pp. 114104, 2024. https://doi.org/10.1016/j.dss.2023.114104

[32] Xu X., Gao Y., and Jia Q., "The Role of Social Commerce for Enhancing Consumers' Involvement in the Cross-Border Product: Evidence from SEM and ANN based on MOA Framework," *Journal of Retailing and Consumer Services*, vol. 71, pp. 103187, 2023. https://doi.org/10.1016/j.jretconser.2022.103187

[33] Yang J., Xiang Y., and Liu C., "Enterprise Sellers' Satisfaction with Business-to-Business Cross-Border E-Commerce Platforms: Alibaba.Com as an Example," *Information Systems*, vol. 122, pp. 102348, 2024. https://doi.org/10.1016/j.is.2024.102348

[34] Ye W., "E-commerce Logistics and Supply Chain Network Optimization for Cross-Border," *Journal of Grid Computing*, vol. 22, no. 22, pp. 317, 2024. https://doi.org/10.1007/s10723-023-09737-z

[35] Yu W., Liu L., Wang X., Bagdasar O., and Panneerselvam J., "Modeling and Analyzing Logic Vulnerabilities of E-Commerce Systems at the Design Phase," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 53, no. 12, pp. 7719-7731, 2023. DOI:10.1109/TSMC.2023.3299605

[36] Zhang C., Wang X., Zhao C., Ren Y., and et al., "Promotionlens: Inspecting Promotion Strategies of Online E-Commerce via Visual Analytics," *IEEE Transactions on Visualization and Computer Graphics*, vol. 29, no. 1, pp. 767-777, 2022. DOI:10.1109/TVCG.2022.3209440

[37] Zhang J., Zhu W., Ahn B., and Zhou Y., "Composite Recommendation of Artworks in E-Commerce Based on User Keyword-Driven Correlation Graph Search," *Tsinghua Science and Technology*, vol. 29, no. 1, pp. 174-184, 2023. DOI:10.26599/TST.2023.9010012

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