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# Segmentation of E-Commerce Users on Cart Abandonment And Product Recommendation Using Double Transformer Residual Super-Resolution Network

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**Abstract:**
*A novel approach named "Segmentation of E-commerce users on Cart Abandonment with Product Recommendation using Double Transformer Residual Super-resolution Network (SEC-CAPR-DTRSRN)" is proposed. This study commences with the collection of e-commerce data from a diverse multi-category store. The pre-processing phase uses Fairness-aware Collaborative Filtering (FACF) to suggest personalized items or content to users based on their preferences through behavior. Following pre-processing, the data undergoes segmentation using the Generalized Intuitionistic Fuzzy c-means Clustering (GIFCMC) technique to categorize users to target-based customer groups. To enhance cart transactions, Double Transformer Residual Super-resolution Network (DTRSN) is introduced for product recommendations. The exploration of cart abandonment identifies potential discord stemming from a misalignment between consumer perceptions and digital site experiences, potentially leading to cart abandonment due to user annoyance. While the DTRSN lacks an explicit adoption of optimization systems for calculating optimal parameters, the manuscript proposes the integration of Polar Coordinate Bald Eagle Search Algorithm (PCBESA). PCBESA is introduced to optimize PCBESA DTRSN, ensuring precise product recommendations. The proposed (SEC-CAPR-DTRSRN) method is implemented, and their performances is rigorously evaluated using key metrics, including mean square error, standard deviation, and mean reciprocal rank (MRR). The proposed method gives 12.78%, 29.85%, and 17.45% lower mean square error and 23.67%, 28.86% and 16.45% higher MRR with existing techniques like segmentation of e-commerce users depending on cart abandonment with product recommendation using collaborative filtering, such as moderating the effect of exorbitant pricing (SECU-CAPR-CF), new top-n recommendation technique for multi-criteria collaborative filtering (PR-MCCF-EC) and reinforcement learning e-commerce cart targeting to reduce cart abandonment in e-commerce (RL-EC-RCA) methods, respectively.*

**Keywords:** *E-commerce, cart abandonment, product recommendation, double transformer residual super-resolution network, polar coordinate bald eagle search algorithm*

## 1. Introduction

Over the past decade, the role of e-commerce markets are exceedingly crucial in the rapidly growing online economy [1, 2]. The availability of 24/7 shopping platforms without limitations has empowered consumers to purchase a wide array of goods anytime from online marketplaces. According to reports from the India Brand Equity Foundation (IBEF), India stands out as a country experiencing higher growth in e-commerce sales [3–5]. The projections indicate that revenues from this sector were expected to surge from USD 39 billion to USD 120 billion through 2021, marking the world's wildest growth rate at an annual increase of 51% in income. Various aspects of online markets, such as customer preferences, usage behaviors, product evaluations, ratings, and shopping cart abandonment, have been thoroughly examined due to the extensive demand in the digital market. Furthermore, with the evolution of the Internet paving the way for new approaches in online commerce, customer lifestyles have undergone a digital transformation [6]. Now, when customers visit physical stores, it's become a habit for them to compare prices between physical and virtual offerings. This habit increasingly leads customers toward digital shopping. A comprehensive survey involving approximately 23,000 consumers global revealed 54% of them create weekly/monthly purchases online, with 60% emphasizing price as the most crucial factor influencing their product choices [7].

It's recognized that the experience of buying a product online differs significantly from traditional brick-mortar shopping. Despite the ease of accessing information, customers are reluctant to pay more. Pricing isn't solely a means to boost sales but is also a pivotal factor impacting a business's most crucial Key Performance Indicators (KPIs) [8, 9]. Conversely, when a potential customer initiates an online checkout but abandons process afore completing transaction, it results in online ordering drop-off [10]. Items added to a shopping cart may/may not eventually be bought and categorized as items consumer 'abandoned.' Online product ratings play a crucial role in shaping purchasing decisions, with lower-rated products experiencing decreased likelihood of being bought [11]. Elements like perceived value, pricing, experiential attributes, symbolic value, and purchase frequency indirectly influence cart abandonment rates [12, 13]. These elements encompass an understanding of reduction magnitude, distribution expenses and sales promotion. Apparent costs are determined based on online feedback and specific metrics [14]. This act of cart abandonment resembles adding products to cart during an online shopping session without completing the purchase [15].

In this paper, by integrating novel DTRSN with segmentation using GIFCMC, the proposed method aims to enhance the accuracy and effectiveness of segmenting e-commerce users. The proposed approach focuses on the novel deep learning method to enhance recommendation systems in E-commerce platforms, leading to more effective and personalized product recommendations for users.

The major contribution of this work is

- In this manuscript, the segmentation of e-commerce users on Cart Abandonment and Product Recommendation (CAPR) using DTRSN is proposed.
- Here, Fairness-aware Collaborative Filtering (FACF) is proposed to suggest personalized items or content to users based on their preferences and behavior.
- GIFCMC is introduced to segment preprocessed data to target-based customer groups. This segmentation facilitates personalized recommendations based on the identified customer groups.
- For product recommendations, novel DTRSN enhances cart transactions and overall user satisfaction during e-commerce transactions.
- To improve product recommendations, PCBESA is proposed to enhance DTRSN weight parameters.

The organization of this study reviews the related work in Part 2, proposed methodology in Part 3, Part 4 proves outcomes and discussion, and Part 5 conveys the conclusions.

## 2. Related Work

Here, we reviewed some papers based on E-Commerce Users (ECUs) on CAPR using deep learning as follows:

Rifat et al. [16] have introduced a ML system designed to help merchants reduce the checkout abandonment rate through informed decision-making and strategic planning. As a key component of this system, they have constructed a robust ML model capable of predicting whether a customer will proceed to checkout after adding products to their cart, based on their activity. Additionally, system offers merchants the ability to delve into the underlying factors driving each prediction output, providing valuable insights for optimization. It has a low mean square error but has a high standard deviation.

Kaya and Kaleli, [17] have explained top-n recommendations in multi-criteria collaborative filtering (MCCF). This revolves around two key aspects, how likes establishing relational structure among products and through examining user inclinations alongside their unique patterns with rating deliveries. To discern rating delivery, product relationships, relation rule mining, and entropy measures were employed, and users' attitudes, tendencies through evaluations were scrutinized using intuitionistic fuzzy sets. This has a high mean reciprocal rank but (MRR) has less accuracy.

Kumar et al. [18] have developed the multivariate pruning technique of web index searching on e-commerce websites using the Knuth Morris Pratt (KMP) algorithm, and they use a variety of web analytics methods in conjunction with machine learning (ML) classifiers to extract patterns from transactional data. Additionally, using log-based transactional data, an evaluation technique based on ML was used to determine how usable e-commerce websites are. The presented method seeks to determine the underlying relationship between the predictor elements and the overall usability of the e-commerce system by utilizing three ML approaches and multiple linear regressions. The presented method was expected to contribute to the economic profitability of the e-commerce industry.

Khan et al. [19] have presented Fuzzy sets/Qualitative Comparative Analysis to explore the relationship between these factors and shopping cart abandonment. Results suggest ad avoidance might serve as a learning device for consumers when they encounter ineffective messages or content, potentially impacting their perception of shopping cart abandonment for a specific brand. It has low root mean square error and low accuracy.

Wang et al. [20] have presented a stimulus-organism-response method to investigate elements impacting customers' inclination towards online-store channel adoption (OSCA) and their choice to purchase from a physical seller. Dual studies were conducted to validate theories posited, focusing on Generation Y consumers in Mainland China. Data were gathered concerning two product categories across distinct timeframes. This has a low square root error but also has a low MRR.

Chawla and Kumar, [21] have presented the existing legal structure in India aimed at safeguarding the interests of online consumers. The freshly introduced regulations appear robust and capable of fortifying the rights of online consumers, thereby potentially fostering the growth of India's e-commerce sector. With a sturdy legal framework and protective measures for consumers in place, the trajectory of e-commerce appears promising. The outcomes of add valuable insights to the realm of e-commerce, and customer rights protection through shedding light on pivotal factors influencing customer trust and loyalty. This has a low mean and has high root square error.

## 3. Proposed Methodology

The proposed manuscript introduces a methodology named SEC-CAPR-DTRSRN. Proposed methodology diagram is displayed in Figure 1. The detailed procedure of the proposed methodology is shown below;

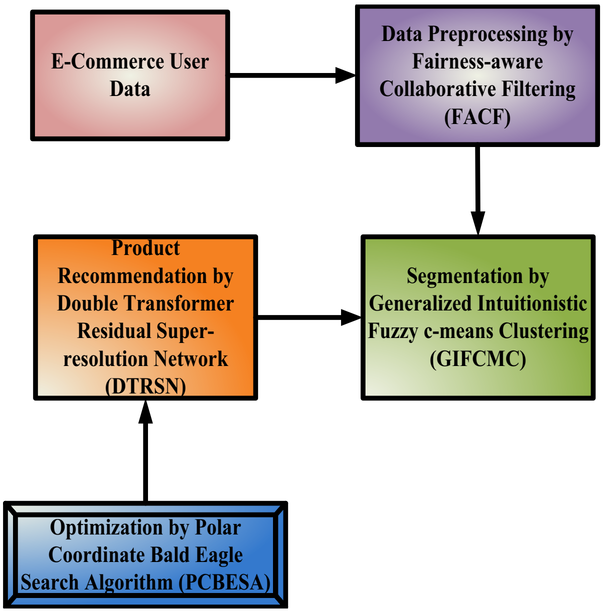


**Figure 1.** Proposed Methodology diagram SEC-CAPR-DTRSRN

### 3.1. Data Collection

Initially,the e-commerce data gathered from a multi- category store [22]. Then, the data are provided to the pre-processing phase.

### 3.2. Data Pre-processing by Fairness-aware Collaborative Filtering (FACF)

The pre-processing stage involves the application of FACF [23] to provide personalized items or content to users based on their preferences and behavior. Fair user embedding's reached by attaching classifier $f_1$ to infer sensitive from user embedding's. Likewise, item classifier $f_2$ to forecasts sensitive information hidden in items' embedding. Assuming each items sensitive labels $d$, present FACF. Filter module is put in to user-items' embedding utilizing classical CF method $N$. The filtered embedding space, forecasts that rating $\hat{m}_{ol}$ of the user $u$ for item $l$ is intended in filtered embedding space n Equation (1)

$$\hat{m}_{ol} = H_O^R H_l + q_o + q_l + \alpha. \tag{1}$$

where $H_l$ denotes item $l's$ filtered item and predicted rating $\hat{m}_{ol}$ of user $o$ for item $l$ intended in filtered embedding space. Dual adversarial modules are implemented to remove the sensitive information from user, items' embedding. Choose filtered embedding input, user classifier efforts to forecast users' sensitive labels, item classifier efforts to forecast pseudo sensitive labels of items. Describe overall loss function in Equation (2)

$$C_{all} = C_\delta(H_O, S_L) - \gamma C_{F1}(H_O, A) - \beta C_{F2}(H_L, D), \tag{2}$$

where the first phrase is accuracy loss, and next phrase is users' sensitive categorization outcomes, and the third term is outcomes from pseudo item labels. Here, the $\gamma$, $\beta$ denotes balancing parameters control outcomes. While $\beta$ equals zero, outcomes is disappear. Here, the optimization of the overall function using minimal value is given in Equation (3)

$$\min_{\delta,J} \max_{F1,F2} C_\delta(H_O, H_L) - \gamma C_{F1}(H_O, A) - \beta C_{F2}(H_O, D), \tag{3}$$

where $C_{F1}(H_O, A)$ is optimizes classifiers and $C_\delta(H_O, H_L)$ denotes employed to develop recommendation accurateness is given in Equation (4)

$$C_\delta(H_O, H_L) = \frac{1}{G} \sum (m_{ol} - \hat{m}_{ol})^2. \tag{4}$$

Pseudo item labels are allocated, deliberate design of loss function $C_{F2}(H_O, D)$. The FACF identifies and groups users based on their preferences and behaviours. This step helps in creating user segments that can be utilized in subsequent stages of the methodology.

### 3.3. Segmentation by Generalized Intuitionistic Fuzzy c-means Clustering (GIFCMC)

The GIFCMC extends traditional Fuzzy c-means [24] clustering by introducing conception of an intuitionistic fuzzy set. Intuitionistic fuzzy sets accommodate not only degree of membership but also the degree of non-membership, a hesitation degree for each data point, offering a more comprehensive representation of uncertainty in the data. The pre-processed data undergo segmentation utilizing GIFCMC to create target-based customer groups. First, the numerical value is transformed into discrete values, then the values are calculated in Equation (5).

$$B_d = c + \frac{m_i - (m_{Min})^d}{(m_{Max})^d - (m_{Max})^d}(f - c) \tag{5}$$

where $(m_{Min})^b$ denotes the dataset $B_d$ minimal value of the dataset in the $b^{th}$volume, and $(m_{Max})^b$ denotes its highest value. $f$ is a user data and $c$ denotes the item data; $b^{th}$ is the volume of the dataset $m_i$. This starts the intuitionistic fuzzification process. The distance between each data-item is calculated once the dataset has been normalized to [0, 1]. The distance matrix for the dataset that has been normalized is shown in Equation (6)

$$R = \{R_I = D_{IJ} * B_{km}, 1 \le I, J \le R\} \tag{6}$$

here, the distance of each data $B$ is calculated. The normalized dataset's distance matrix is called $D_{IJ}$. The cluster matrix's reciprocation is provided in Equation (7).

$$V = \frac{1}{Rec} \tag{7}$$

where, the cluster value matrix for each dataset $z_i$ is provided by the matrix $V$, and reciprocation of $Rec$ matrix is denoted by record dataset. Consider the record as a candidate rule if the frequency of the record exceeds the AU. The clustering criterion comes next in Equation (8).

$$K_a = \sum_{L=1}^{b} \sum_{J=1}^{h} X_{LJ}(m_J, c_J) \tag{8}$$

where, $m_J = (\mu_i, v_i, \pi_i)$ is the cluster method representation of the $J^{th}$ data-point, which has $X$D features, with each feature having cluster re-presentation. These candidate criteria are used to create positive and negative clusters; any record that does not fit the candidate guidelines will be regarded as an outlier record and it is shown in Equation (9)

$$\sum_{I=1}^{B} v_{iL} > 0, 1 \leq L \leq d \tag{9}$$

where $v_{iL}$ membership matrix of order $L$, and $\sum_{I=1}^{B}$ is the set of cancroids of these $d$ clusters. Lagrange's state of unknown multipliers G-IFCM is utilized in order to group the heart disease patients record using the formula given below Equation (10)

$$\mu_L = \frac{\sum_{I=1}^{B} v_{IL}^{n} \mu_{zI}}{\sum_{I=1}^{B} v_{IL}^{n}} \tag{10}$$

where $v_{IL}^{n}$ is the number of groups in Cluster $\mu_{zI}$ that have the leading class label, $\mu_L$ denotes total number of clusters, $B$ and signifies the number of examples in cluster.

The final output is a set of clusters, each containing data points assigned to it based on their membership degrees. In the context of the SEC-CAPR-DTRSRN methodology, GIFCMC is applied to segment the preprocessed e-commerce data into customer groups, helping to identify patterns and preferences that can be used for targeted product recommendations using the subsequent DTRSN.

### 3.4. Product Recommendation by Double Transformer Residual Super-resolution Network (DTRSN)

The DTRSN [25] is employed to enhance cart transactions by recommending products. Cart abandonment may stem from discrepancies between consumer perceptions and digital site experiences, leading to frustration and cart abandonment. The DTRSN takes as input the segmented and pre-processed e-commerce data, which includes information about user behaviors, preferences, and historical interactions with the platform. The input data is passed through an embedding layer to convert categorical variables and user_item interactions into a continuous vector representation suitable for deep learning. The core of the DTRSN lies in its Double Transformer architecture. The Transformer model is a powerful Neural Network (NN) architecture originally intended for Natural Language Processing (NLP) but adaptable to various sequence-based tasks. Remaining connections are engaged to solve vanishing gradient issue, aid training of deep networks. Such connections permit method to learn remaining mappings, making it easier to optimize and improve the flow of information through the network. The DTRSN is trained using a suitable loss function that calculates the dissimilarity among the predicted recommendations and the actual user behavior (e.g., purchase history). The optimization algorithm is employed to optimize the model's parameters during training. The mathematical representation is as follows;

The module can extract concealed weight information in the spatial area. Recombine spatial features create feature vectors through spatial similarity in accordance with the correlation of the features. Thus, it is given by the Equation (11)

$$x_i = [\alpha_r(y_i), \beta_r(s_{mi})] + [\alpha_r(y_i), \beta_r(s_{ai})] \tag{11}$$

where, $\alpha$ and $\beta$ indicates embedded purposes of feature then global association. $s_{mi}$ and $s_{ai}$ represents the relationship between $y_i$, thus the pixel is given by the Equation (12)

$$Z_{SR}(x, y) = k\left(K_{LR}(x', y'), Q(x, y)\right) \tag{12}$$

$Z_{SR}(x, y)$ Indicates the pixel value of super-perseverance, $k$ is the feature mapping function, $Q\ (x, y)$denotes weight calculation segment of pixel, $K_{LR}$ is the feature vector on corresponding pixels. Projection conversion function $M$ is expressed using Equation (13)

$$(x', y') = M(x, y) \tag{13}$$

where, $M$ denotes Projection conversion function, and $x, y$ denotes weight estimation. Each body region's final features are obtained, and then we feed them into the layer, which consists of two entirely associated connection layers which are given by the Equation (14)

$$D_{id} = -\sum_{l=1}^{L} \sum_{f=1}^{F} x_f . \log(\hat{x}_l) \tag{14}$$

where, $F$ and $L$ denote the total number of recognized samples and samples sets, $x_f$ represents the dual label of the sample, $\hat{x}_l$ and indicates the probability prediction.

The utilization of DTRSN in this context aims to provide a sophisticated and personalized approach to product recommendations, with the ultimate goal of reducing cart abandonment and enhancing overall user satisfaction during e-commerce transactions.

### 3.5. Optimization of DTRSN by Polar Coordinate Bald Eagle Search Algorithm (PCBESA)

The PCBESA [26] is an optimization method for fine-tuning the parameters of the DTRSN to enhance its effectiveness in making precise product recommendations. PCBESA method is used to enhance weights parameters [$\alpha$ and $\beta$] of proposed DTRSN. Below is a general description of the PCBESA and its steps:

***Step 1*:** Initialization

The initial population of PCBESA is, initially generated by randomness. Then, the initialization is derived as Equation (15)

$$\rho = \begin{Bmatrix} \rho_{1,1} & \rho_{1,2} & \cdots & \rho_{1,u} \\ \rho_{2,q} & \rho_{2,2} & \cdots & \rho_{2,u} \\ \rho_{n,1} & \rho_{n,2} & \cdots & \rho_{n,u} \end{Bmatrix} \tag{15}$$

where, $\rho$ is the poplar's diameter of the $j$th initialization position.

***Step 2***: Random generation

The input weight parameter [$\alpha$ and $\beta$] is produced at random using PCBESA method.

***Step 3:*** Fitness function

It creates a random solution from initialized assestments. It is assesssed utilizing the optimizing parameter. This is calculated using Equation (16):

$$Fitness\ Function = optimizing[\alpha\ and\ \beta] \quad (16)$$

***Step 4***: Exploration Phase:

In the initialization phase, the PBES algorithm must also regulate the border, and each individual can be dispersed throughout the entire search space. Thus, the polar angle $F$ has a value range of $(0, 2\pi)$. In addition, boundaries must be defined for the polar diameter in order to prevent the PBES algorithm from exceeding them during the optimization process. Then the exploration is given as Equations (17), (18), and (19):

$$\rho_{j,New} = \rho_j + W_1 * (\rho_j - \rho_{Mean}) + N_1 * (\rho_j - \rho_{j+1}) \quad (17)$$

where, $\rho_{Best}$ denotes the area that was found to be the greatest choice for the bald eagles to choose during the prior search; $\rho_j$ indicates where the bald eagles are located; $\rho_{j,New}$ is where the bald eagles have relocated; $\rho_{Mean}$ denotes position of bald eagles' average distribution following previous exploration; $n_1$ and $w_1$ symbolize arithmetic normalization of $\eta$ and $\rho_{j+1}$ is the $j$th bald eagles' most recent revised position.

$$n_1 = \frac{\eta_1}{\max(|\eta_1|)} \quad (18)$$

where, $n_1$ symbolize the arithmetic normalization of $\eta$; $\eta_1$ denoted as every bald eagles location is updated.

$$\eta_2 = rand * \cos(\theta) \quad (19)$$

where, $\theta$ by renewing, the specific position is update; $\eta_2$ denoted as every bald eagles location is updated and $Rand$ is a random integer between 0 and 1.

***Step 5***: Exploitation phase for optimizing [$\alpha$ and $\beta$]:

Retention and replacement are the two scenarios that exist. Proceed with the first operation if novel fitness value is determined to be better than present fitness value; if not, proceed with the second operation. Instead of using the Cartesian coordinate system, the PBES updates individual positions in the polar coordinate system. The location of person is derived through updates. Individuals' update speeds will increase significantly as a result, and convergence efficiency will rise by Equations (20), (21), and (22):

$$\rho_{j,new} = rand * \rho_{best} + w_2 * (\rho_j - z_1 * \rho_{mean}) + n_2 * (\rho_j - z_2 * \rho_{best}) \quad (20)$$

where, $\rho_{j,new}$ is where the bald eagles have relocated; $\rho_{mean}$ denotes position of bald eagles' average distribution following previous exploration; $\rho_{best}$ denotes area that was found to be the greatest choice for the bald eagles to choose during the prior search; $\rho_j$ indicates where the bald eagles are located; $rand$ is a random integer between 0 and 1; $n_2$ and $w_2$ needs to be compared to one another's bald eagle and $z_1$ and $z_2$ are the enhancement coefficient, which is taken by all of them to be 2.

$$n_2 = \frac{\eta_2}{\max(|\eta_2|)} \quad (21)$$

where, $n_2$ needs to be compared to one another's bald eagle and $\eta_2$ is denoted as every bald eagles, location is updated.

$$\eta_2 = r_1 * \cos g(\theta)\eta_2 \quad (22)$$

where, $r_1$ is a random integer between AU 0; $\eta_2$ is denoted as every bald eagles' location is updated and $Cosg$ is denoted by renewing, the specific position is updated. Then the specific position is updated is given as Equation (23):

$$\theta_{j+1} = \beta * \theta_j \pm 2 * \cos^{-1}(2 * rand - 1) \quad (23)$$

here,$\beta$ denotes coefficient of disturbance, with values among 0, 2; $Rand$ is a random integer between 0; $\theta_{j+1}$ the new role for each individual is established and $\theta_j$ needs to be compared to one another.

The PCBESA aims to efficiently explore the solution space and find optimal parameters for the DTRSN, enhancing its performance in the specific task of product recommendation in e-commerce. The algorithm draws inspiration from the bald eagles' hunting behavior and their ability to navigate and search effectively in their environment.

## 4. Performance Evaluation

The experimental outcome of the suggested technique is discussed in the section. The simulations were carried out on Windows 7, an Intel Core i5, and 8GB of RAM. The suggested method was tested using performance metrics in MATLAB. The proposed SEC-CAPR-DTRSRN method is implemented, and their performance is evaluated utilizing metrics likes MSE, standard deviation, and MRR. The obtained outcome of suggested SEC-CAPR-DTRSRN analyzed with existing ML-MCA-EC [16], PR-MCCF-EC [17], and ML-ARM-EC [18] methods, respectively.

### 4.1. MSE

It measures average squared difference among forecasted and actual values. In context of the proposed method, MSE can be utilized to assess accurateness of product recommendations. This is calculated in Equation (24),

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (24)$$

here, $N$ signifies total number of data points, $y_i$ implies actual value, and $\hat{y}_i$ signifies forecast value.

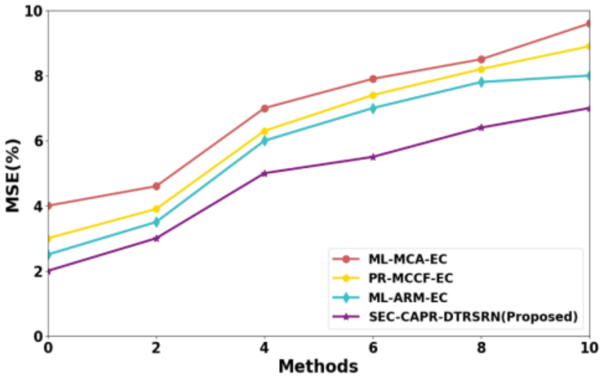


**Figure 2.** MSE analysis

### 4.2. Standard Deviation

It is a scale of amount of variation in a set of values. In context of performance evaluation, it provides insights into the consistency of the recommendations. It is calculated by Equation (25),

$$\sigma = \sqrt{\frac{\sum_{l=1}^{N}(x_i - \bar{x})^2}{N}} \tag{25}$$

here, $N$ denotes total number of data points, $x_i$ implies all individual data points, and $\bar{x}$ signifies mean of data.

### 4.3. Mean Reciprocal Rank (MRR)

MRR is a metric commonly used to evaluate the effectiveness of recommendation systems in ranking items. It measures how well the system ranks the relevant items higher in the list. It is given in Equation (26),

$$MRR = \frac{1}{|q|}\sum_{i=1}^{|q|}\frac{1}{rank_i} \tag{26}$$

here, $|q|$ denotes number of queries, $rank_i$ implies rank of first relevant item for $i_{th}$ query.

Figure 2 shows MSE analysis. The SEC-CAPR-DTRSRN gives a low mean square of 20.78%, 19.67% and 27.80% with existing ML-MCA-EC, PR-MCCF-EC, and ML-ARM-EC methods, respectively. Lower values are better, as they signify higher accuracy and consistency in the recommendations.

Figure 3 shows standard deviation analysis. The SEC-CAPR-DTRSRN gives low standard deviations of 30.78%, 25.67% and 17.80% with existing ML-MCA-EC, PR-MCCF-EC, and ML-ARM-EC methods, respectively.

Figure 4 displays MRR analysis. The SEC-CAPR-DTRSRN gives high MRR of 20.48%, 23.57% and 19.80% with existing ML-MCA-EC, PR-MCCF-EC, and ML-ARM-EC methods, respectively.

## 5. Discussion

The SECU-CAPR-DTRSRN introduces a unique and advanced approach to enhance user experience and transaction success. Segmentation is a critical stage

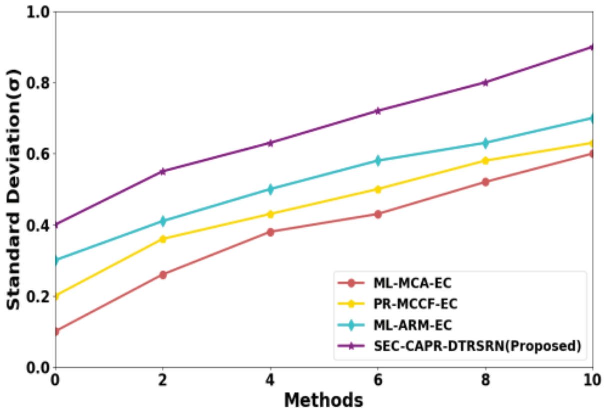


**Figure 3.** Standard deviation analysis

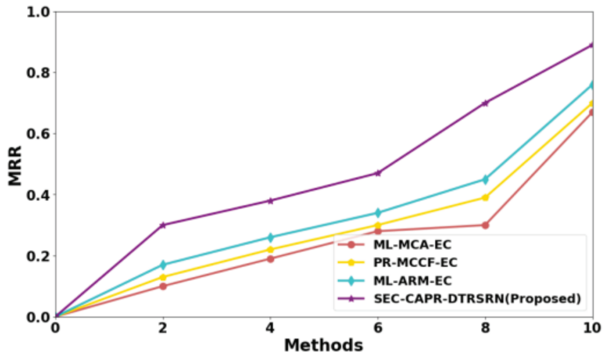


**Figure 4.** MRR analysis

in understanding, and catering to diverse necessities, and behavior of ECU. By focusing on cart abandonment patterns, the segmentation process aims to detect distinct user groups with common characteristics. The integration of DTRSRN in the proposed system signifies a sophisticated and state-of-the-art approach. The model's ability to capture intricate patterns and features in user behavior enhances the precision of product recommendations. By focusing on cart abandonment, the methodology acknowledges the importance of identifying and addressing the root causes behind this behavior. Understanding the reasons for abandonment is crucial for implementing operative approaches to reduce it. The ultimate goal of the proposed methodology is to positively impact conversion rates by reducing cart abandonment. A more personalized and dynamic approach, facilitated by DTRSRN and reinforcement learning, holds the potential to create a more seamless and satisfying shopping experience.

## 6. Conclusion

The SECU-CAPR-DTRSRN is proposed. Through GIFCMC, the user base is effectively segmented into target-specific groups. This user-centric approach enables more personalized and targeted interventions. The utilization of the DTRSRN for product recommendations demonstrates a commitment to employing advanced deep learning techniques. This enhances the system's ability to understand user preferences and deliver more accurate and relevant product suggestions. Implementation and evaluation of the proposed method utilizing metrics likes mean, MSE, standard deviation, and MRR provide a quantitative assessment of its effectiveness. Such metrics enable complete understanding of system's accurateness, consistency, and ranking quality.

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