Development of a Federated Learning and Knowledge Graph-Based Personalized E-Commerce Recommendation System Using PTB-MFA

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E-commerce platforms require accurate and personalized recommendation systems while ensuring user privacy and scalability. Traditional centralized recommendation models face challenges related to privacy risks, data heterogeneity, and limited personalization. To address these limitations, this study proposes a Painting Training-Based Optimization with Modified Federated Averaging (PTB-MFA) framework that integrates federated learning with knowledge graph embeddings for privacy-preserving personalized recommendation. The proposed method captures complex semantic relationships among users, products, and categories while enabling adaptive client-level personalization. Experiments conducted on an e-commerce personalized recommendation dataset demonstrate that PTB-MFA outperforms existing methods, achieving improvements of 16.9% in Click-Through Rate, 19.9% in user engagement, and 6.37% in Mean Average Precision. The results confirm that the proposed framework effectively balances personalization accuracy, privacy preservation, and computational efficiency for next-generation e-commerce systems.

Povzetek: Raziskava predstavlja federirani pristop za priporočilne sisteme v e-trgovini, ki z uporabo grafov znanja izboljšuje personalizacijo ob hkratnem varovanju zasebnosti in večji učinkovitosti.

1 Introduction

The entire number of sales in EC systems has increased dramatically in recent years, owing to the proliferation of online technologies and services available. With the development of large enterprises, competition for both profitability and obtaining clients has strengthened. Companies have focused on broadening product availability, providing attractive discounts, expediting payment methods, and restructuring customer queries to stay profitable [1]. E-Commerce has evolved into an enabler of national consumption and economic growth. The growth in E-Commerce will significantly change consumers' lifestyles and consumption behaviour [2]. E-commerce has experienced several stages. The first was the user-based stage, which was categorized by e-commerce platforms creating membership systems as a means of generating revenue from users. The second stage was a volume-based model. The final level was statistics , and the databases has a considerable number of users viewing and purchasing data as a consequence of the widespread distribution of e-commerce algorithmic suggestions across various websites. The complexity of the information structure and the enormous volume of data are too much for standard single-machine algorithms to handle. However, the initial computation and storage paradigm must be updated and enhanced due to the high cost of powerful processors [4]. The term "e-commerce customization" describes how material, suggested products, and promotions are presented on e-commerce websites in a way that is tailored to the user's browser preferences, past purchases, personal traits, and other information. By analyzing consumer purchase intents and developing marketing strategies, this technique assists in determining a company's sales and growth [5]. Customers now have more options because of the growth of online retailers, which makes it simple for them to compare goods and costs. Online marketers are always being pushed by the expansion of virtual retailers to enhance their tactics by providing discounts and tailoring product recommendations to outperform rivals [6]. To offer personalized service, maintaining customer contact, collecting complete information, and providing integrated marketing, direct promotion, personalized assistance, and timely service are essential. This fosters a sense of value and improves consumer fulfillment and assistance [7]. To stay competitive in today’s highly volatile and fast changing world, businesses must develop accurate forecasts of customers behavior. Personalization offers an exciting potential through the immense data collected and it allows concentration on the customer to act with precision and customization [8]. Although many social and business operations are now conducted online, security of data and privacy laws are crucial and in great demand globally. For service suppliers, using and disclosing personal data to third parties for recommendation systems presents numerous logistical challenges [9]. E-commerce decreases individual mobility while expanding the number of transporters going through cities. In the setting of e-commerce, doing repeated distribution circuits with a limited number of trucks is more effective than having numerous cars travel separately among stores, as is customary in standard business [10].

Research aims and organization: Through federated learning and knowledge graph integration, the research attempts to create the PTB-MFA framework to improve personalized e-commerce suggestions, guaranteeing high accuracy, user privacy, and adaptability.

Organization of the research: Section 2 presents the related works; Section 3 shows the methodology; Section 4 shows the results and discussions; and Section 5 concludes the research.

2 Related works

The research evaluated DL -based recommendation methods in e-commerce by examining CNN, RNN, and sentiment analysis methodologies [11]. The findings showed that these DL methods greatly improve recommendation performance, solve issues like initialization and insufficient evidence, and offer online businesses more precise and user-focused product recommendations. DL and personality analytics to develop a hybrid content-based image retrieval and DSS for e-commerce [12]. The research resulted in better business decision-making and tailored recommendations with the highest accuracy once the Dynamic Adjustment Models were applied, which combined VGG-Net and Inception-Net. A customized recommendation framework of online products was developed through distributed storage technologies [13]. The framework improved data effectiveness, customization to users, and convenience of payment in massive-scale e-commerce settings by improving rule-based logic and knowledge models in system applications. RF and GBDT were the ML methods used to progress an combined modified recommendation framework for online business sites [14]. These findings demonstrate that the DL techniques enhanced the accuracy of prediction and decreased sparsity of the recommendations. The research strengthens customized e-commerce suggestions that were attained by the application of collaborative filtering and AI [15]. The findings revealed that there was a growth in accuracy, a decrease in data sparsity, an enhancement in suggestion diversity and better reliability of the systems when semantic information, and confidence and preference evaluation of consumers are used. The research utilized a retrieval-based recommendation system that integrated collaborative filtering, recognition, and Bayesian ranking, including LightGBM and DNN models [16]. The findings of the research showed that LightGBM was superior to DNN by increasing recommendation accuracy and personalization measurements with higher values.

In the research [17], the domain knowledge and the information on user activity were used to create a DL-based cognitive personalized recommendation system. The findings revealed better memory, accuracy and precision in prediction, and it was able to bridge the semantic gap between recommendations under multidimensional conditions. It developed a MCDM-based online store recommendation mechanism, which incorporated a combination of COCOSO, EDAS, MAIRCA, MABAC and CRITIC weighting [18]. The findings provided high consistency of scores, accuracy, and effectiveness in decision support and appropriate product recommendations. The subjective estimation, and group filtering, along with segmentation, were utilized to create a cross-platform tailored suggestion engine based on E-commerce and social media data [19]. The results proved that integrated analysis of data increased the accuracy of customer profiles, accuracy of advice, and effective implementation of societal ecommerce. The research created an advanced system of generating garment fashion suggestions relying on the thought process of Fuzzy Logic, GAs and SVR [20]. The outcomes depicted precise, versatile and communal tailoring of garments, which enhanced personalization and effectiveness of the form through the strategy of continued collaborative upgrading. The integration of the ConvLSTM model with lateral federated instruction was used to provide safe and precise multi-dimensional demand forecasting [21]. The method increases forecasting accuracy while limiting data privacy leaks. The outcomes demonstrate increased prediction accuracy, less disruptive impact, and encouragement for long-term e-commerce growth. The federated learning was used in the research to provide a sophisticated selection framework for open development in international e-commerce. The method reliably enhances creative choices, and the outcomes demonstrate enhanced forecast accuracy and successful multi-company coordinated efficiency [22]. Recent work published in Informatica has emphasized the role of hybrid learning paradigms that balance personalization accuracy with privacy preservation in distributed e-commerce environments. In particular, the study in [25] demonstrates that combining structured relational modeling with decentralized learning can significantly enhance recommendation robustness while complying with data privacy constraints, which aligns with the motivation of the proposed PTB-MFA framework.Table 1 depicts the state-of-art literature. Despite these advances, existing approaches do not jointly address privacy preservation, semantic reasoning, and client-level personalization within a unified federated learning framework.

Table 1: State-of-art literature review of E-commerce recommendation system

Reference	Aim	Method	Result
Almahmood & Tekerek[11]	To evaluate DL-based recommendation methods for improving e-commerce personalization.	CNN, RNN, and sentiment analysis models.	Improved recommendation accuracy and personalization; addressed issues like evidence insufficiency and initialization.
Bagwariet al. [12]	Create a hybrid content-driven image search and decision-support platform for e-commerce.	DL with VGG-Net and Inception-Net.	Achieved 98.2% accuracy in personalized recommendations and decision support.
Yang [15]	To enhance personalized e-commerce recommendations through AI and collaborative filtering.	Semantic information fusion with consumer confidence and inclination analysis.	Improved accuracy, diversity, and reliability in recommendations.
Nguyenet al. [16]	To design a retrieval-based recommendation model integrating combined filtering and Bayesian position.	LightGBM and DNN.	LightGBM outperformed DNN with higher customization and accuracy.
Bączkiewiczet al. [18]	To develop an MCDM-based online store recommendation mechanism.	COCOSO, EDAS, MAIRCA, MABAC with CRITIC weighting.	Achieved high accuracy, consistency, and effectiveness in decision support.
Zhaoet al. [19]	To establish a cross-platform customized recommendation engine integrating e-commerce and social media.	Subjective estimation, group filtering, and segmentation.	Enhanced customer profile accuracy and social commerce performance.
Zhang & Guo[22]	To design a federated learning framework for global open innovation in e-commerce.	Federated Learning-based collaborative selection framework.	Improved multi-company coordination and forecast accuracy.

2.1 Problem statement

Even through DL-based e-commerce recommendation systems have made great strides, issues including data sparsity, restricted customization, and privacy hazards continue to restrict accuracy and flexibility in distributed systems [14]. To improve safe, accurate, and user-focused recommendations, federated learning and optimization techniques must be included [16, 22]. By strengthening personalization, protecting user privacy, and boosting model convergence, the suggested PTB-MFA methods address these gaps. It effectively strikes a balance between local and global learning, lowers data sparsity, improves suggestion accuracy, and guarantees safe, flexible, and effective e-commerce personalization in dispersed client environments.

2.2 Research design and objectives

The primary objective of this study is to design a privacy-preserving and scalable personalized recommendation system for e-commerce platforms.

Specifically, the research aims to:

(i) integrate federated learning with knowledge graph embeddings to enhance semantic representation,

(ii) improve client-level personalization using PTB-based optimization, and

(iii) evaluate performance gains over existing recommendation models using standard metrics such as CTR, NDCG, and MAP.

3 Methodology

The proposed method uses Federated Learning, Knowledge Graph Embedding, and PTBO to create a privacy-preserving and personalized e-commerce recommendation system. Through adaptive learning, feature extraction, and global–local model optimization utilizing the MFA framework, it promotes personalization, protects data privacy, and increases recommendation accuracy. Figure 1 depicts the overall process of methodology. Regarding scalability, the proposed PTB-MFA framework is designed to scale horizontally with increasing numbers of clients, as model aggregation depends on parameter updates rather than raw data transfer. Compared with centralized deep learning approaches, PTB-MFA reduces communication bandwidth requirements and supports asynchronous client participation, making it suitable for large-scale and time-sensitive e-commerce applications.

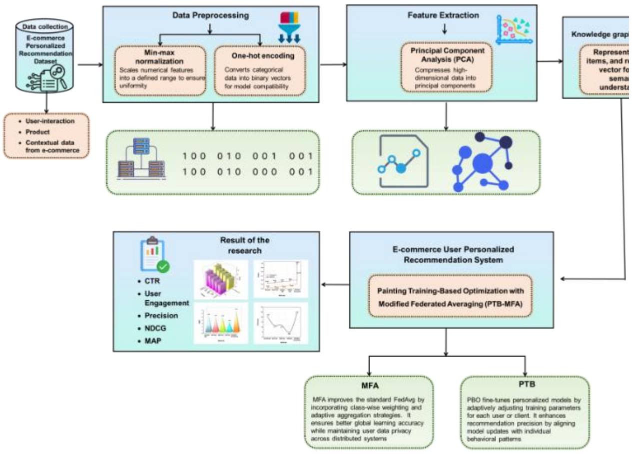

Figure 1: Methodology flow.

3.1 Dataset description

The E-commerce Personalized Recommendation Dataset utilized in the research is obtained from Kaggle (https://www.kaggle.com/datasets/zara2099/e-commerce-personalized-recommendation-dataset/data). User interactions, product details, and contextual behavior inside an online store are represented by the 1,000 entries and 22 columns in this dataset. To effectively evaluate the model's effectiveness, the dataset was divided into 80% training and 20% testing. It is intended to aid in the research and creation of models for tailored systems of recommendations that strike a compromise between privacy and accuracy. Every record documents the intricate connections between users, goods, categories, and contextual elements that affect consumer behavior and customized results.

3.2 Preprocessing techniques

3.2.1 Min-max normalization

In E-commerce Personalized Recommendation, the Min-Max normalization approach converts the values of the large data attributes into innovative, smaller amounts positioned within an initial spectrum. It is acknowledged that the normalization preserves every relationship in the E-commerce under consideration. Each value in the feature under consideration is mapped to a new normalized value by the following Equation (1).

$$T' = \frac{T - \mathrm{min}_A}{\mathrm{max}_A - \mathrm{min}_A}(\mathrm{new\_max}_A - \mathrm{new\_min}_A) \tag{1}$$

Where max_A is the highest integer for the supplied attribute, T is the original value for the feature, and T' is the new normalized value. min_A is the minimal value for the provided characteristic, A. While $\mathrm{new\_max}_A$ and $\mathrm{new\_min}_A$ indicate the extreme and least values for the newly considered rangeA in E-commerce Personalized Recommendation.

3.2.2 One-hot encoding

One-hot encoding is an effective approach that converts category numbers into binary vectors, guaranteeing that the method correctly interprets behavioral category's contribution to personalized recommendation outcomes. One-Hot Encoding is used to preprocess structured data like product types, organizations, and user preferences prior to being uploaded into the federated learning architecture. Unlike label encoding, one-hot encoding does not include ordinal associations that could bias estimations for the E-commerce personalized recommendation dataset. One-hot encoded features to represent categorical before local training are depicted in Equation (2).

$$i(y) = \frac{1}{1 + e^{-(x_1 y_1 + x_2 y_2 + \cdots + x_0 y_0)}} \tag{2}$$

Where, $i(y)$ is the output of one-hot encoding for category y, $y_1, y_2, \ldots, y_o$ are the one-hot encoded components of a categorical variable and $x_1, x_2, \ldots, x_o$ denote the associated weights, each component vector is represented in Equation (3).

$$x_j = [0,0,0, \ldots, \ldots, 1,0,0] \tag{3}$$

Here, j represents the currently selected category position, and the overall vector length is equivalent to the amount of distinct categorical values.

3.3 PCA for extraction feature

The PCA is a data augmentation technique that reduces the high-dimensional data to speed up computation and reduce the risk of overfitting while retaining the most essential personalized patterns from user-product interactions. The initial E-commerce personalized recommendation dataset $Z_{s\times t}$ is structured as a matrix consisting of s rows and t columns in the E-commerce platforms, as shown in Equation (4).

$$Z_{s\times t} = \begin{pmatrix} x_{11} \cdots & x_{1t} \\ \vdots & \ddots & \vdots \\ x_{s1} & \cdots & x_{st} \end{pmatrix} \tag{4}$$

The prediction outcomes can be significantly influenced by the significant length variation in scale among features, such as product prices and user ratings. The component $Z_{s\times t}$ is standardized to employ the better use of PCA and transformed into a standardized matrix Z^* in E-commerce personalized recommendation system, represented in Equation (5).

$$Z_{l,m}^* = \frac{Y_{l,m} - \mu_m}{\sigma_m}, l = 1,2, \ldots, s; m = 1,2, \ldots, t \tag{5}$$

The standardized value is denoted as $Z_{l,m}{}^{*}$. $\mu_m$and σ_m represent both the average and variance of the original E-commerce data. The correlation matrix derived from the standardized dataset is computed as $N_{s\times t} = Z^{*T}Z^{*}$. Equation (6) represents the effectiveness rate of each primary component (η) in E-commerce personalized recommendation dataset.

$$\eta_k = \frac{\lambda_k}{\sum_{k=1}^{s}\lambda_k} \tag{6}$$

Where η_k is the effectiveness rate of the k-th major component, λ_k is the eigenvalue corresponding to the k-th principal component, $\sum_{k=1}^{s}\lambda_k$ is the sum of all eigenvalues, representing the total variance across principal components.

3.4 Capture and represent complex semantic relationships among entities using KGE

KGE techniques are essential for effectively describing complicated data structures. These techniques use algorithms like Node2Vec to translate the nodes, components, and associations of an information graph into an uninterrupted vector space, allowing the framework to comprehend semantic linkages between individuals, businesses, and classes. Deeper semantic connections among people and things can be captured by the system thanks to KGE approaches, which offer low-dimensional visualizations of connections and entities in the knowledge graph for improving personalization by significant interaction knowledge. The distance between two nodes in relation to their link in the embedding space is quantified by a score function defined by each KGE method. By guaranteeing that nodes (such as user and selected product) that have relationships in the knowledge graph stay close in the underlying dimension while unrelated nodes remain apart, this scoring method inside the suggested federated suggestion framework is consistent in e-commerce platforms. For determining the knowledge graph embedding R, minimize the objective function, as shown in Equation (7).

$$\Psi(r) = \sum_{j=1}^{o}\left[\alpha_j\left\|r_j - \hat{r}_j\right\| + \sum_{(j,k)\in F}\beta_{j,k}\left\|r_j - r_k\right\|^2\right] \tag{7}$$

Where α and β values regulate the weights of the knowledge graph and embedded words, and $R = (r_1, r_2, \dots, r_{o)}$is the learnt information graph embedding vector. Before being retrofitted, the phrase vectors in $R$are first initialized to match the vectors in R^2.

3.5A Novel PTB-MFA framework enhances personalization at the client level while leveraging global patterns

3.5.1 MFA

The MFA approach enhances the personalization and reliability of the privacy-preserving e-commerce recommendation mechanism by increasing model accumulation at the client stage while maintaining global uniformity. The MFA framework uses category-weighted parameter accumulation to provide tailored e-commerce recommendations, which is represented in Equation (8).

$$x_{t,u+1}^{m=M,d} = \sum_{l=1}^{L}\frac{o_l^d}{o^d}x_{l,u}^{m=M,d} \tag{8}$$

Where$x_{t,u+1}^{m=M,d}$ represents the updated global model parameter at $(t, u+1)$, d is the position for the secret nodes in the last recommendation layer, $m$is the position of elements in a structure with M layers, $o_l^d$is the local contribution weight of the l^{th} client, L is the total amount of participating clients.

3.5.2 PTBO

Starting phase: PTBO is a population-scale technique that mathematically models every participant in the e-commerce system as a potential solution employing a vector, representing possible configurations of personalized models for each client (user node). For expressing the complete population, use a matrix as shown in Equation (1). The algorithm starts by initializing the positions of each PTB. Painting consumers'' solutions have been assessed using the challenge's objective function, as shown in Equation (9). The assessed outcomes of the objective function can be expressed as a vector, represented in Equation (10):

$$W = \begin{bmatrix} W_1 \\ \vdots \\ W_j \\ \vdots \\ W_M \end{bmatrix}_{M\times n} = \begin{bmatrix} W_{1,1} \dots W_{1,c} \dots W_{1,n} \\ \vdots \quad \ddots \quad \vdots \quad \iddots \quad \vdots \\ W_{j,1} \cdots W_{j,c} \cdots W_{j,n} \\ \vdots \quad \iddots \quad \vdots \quad \ddots \quad \vdots \\ W_{M,1} \cdots W_{M,c} \cdots W_{M,n} \end{bmatrix}_{M\times n} \tag{9}$$

$$W_{j,c} = ka_c + q.(va_c - ka_c) \tag{10}$$

Where W is the PTBO demographic matrix, M is the amount of local personalized method, is the jth dimension in the search space (decision variable), $W_{j,c}$is the jth dimension of the cth painting recommendation system (possible solution), n is the total number of choice variables, q is a selection of numbers in the interval [0, 1] and $va_c$is the lower bound and upper bound of the c^{th} choice variable, respectively. For the purpose of ensuring enhanced customization accuracy, individual user adaptation, and privacy preservation across distributed nodes, the objective equation of the problem is used to assess the painting candidate solution proficiency in developing the federated e-commerce recommendation model represented in Equation (11).

$$E = W = \begin{bmatrix} E(W_1) \\ \vdots \\ E(W_j) \\ \vdots \\ E(W_M) \end{bmatrix}_{M\times 1} \quad (11)$$

Where, E is the vector of evaluated objective function values reflecting recommendation system performance, $E(W_1)$ is the objective function of the first candidate solution, $E(W_j)$ is the function measuring the personalized recommendation system, $E(W_M)$ is the total number of painting clients participating in the federated procedure.

Phase 1-Global knowledge adaptation (Exploration): In the training painting procedure, every localized consumer communicates using a global knowledge component created from the Knowledge Graph. This allows every client to incorporate structural as well as cognitive considerations while preserving data privacy. Phase one of the PTBO emulates the relationships between teachers and students and modifies the positions accordingly. The new locations are calculated based on Equations (12) and (13) subject to training coefficients, teacher influence, and other characteristics. If the new position raises the desired function value, it will replace the current position as presented in Equation (14), thereby increasing the effectiveness and efficiency of the search.

$$l(s) = q.\frac{s}{S} \quad (12)$$

$$W_j^{o1} = W_j + l(s).\left(J - W_j\right), j = 1,2,\dots,M \quad (13)$$

$$W_j = \begin{cases} W_j^{o1}, E_j^{o1} < E_j \\ W_j\ , else \end{cases} \quad (14)$$

Where, $l(s)$ is the knowledge constant, q signifies the persistent scaling feature, s is the current step through federated training in e-commerce, S is the total amount of optimization repetitions, W_j^{o1} is the efficient tailored model weight vector, W_j represents the present weighted vectors of the jth combined consumer, J is the global best outcome, and M denotes the total number of connected clients.

Phase 2-Personalized fine-tuning: After broad adaptation, each client executes personalized adaptation using individual client interaction data. This phase improves the individualization element of objective by fine-tuning model parameters to match local user preferences. New positions are calculated and replaced if they increase the objective function value, represented in Equation (15). This iterative procedure refines positions and improves the algorithm's exploitation capabilities. PTB achieves a better equilibrium between the two processes, leading to improved optimization and resolution performance.

$$W_j^{o2} = W_j + (1 - 2q).\left(\frac{va - ka}{s}\right) \quad (15)$$

Where, W_j^{o2} is the updated weight of the jth model, va and ka are the best and current positions of the ath consumer in E-commerce. As demonstrated in Algorithm 1, the PTB-MFA technique creates a highly personalized, knowledge-aware, and privacy-preserving e-commerce suggestion system that employs KGE and federated instruction to improve recommendation preciseness, flexibility, and particular user personalization in distributed networks.

Algorithm 1: PTB-MFA

```
  Initialize global model weights w_global randomly
  Initialize server momentum vector v = 0
  FOR round t = 1 TO 200 DO
    BEGIN
      Select subset S_t of clients such that |S_t| = C × M = 3
      Initialize empty list Uploads = { }
      FOR each client i ∈ S_t IN PARALLEL DO
        BEGIN
          Send current global model w_global to client i
          (Δ_i, n_i, q_i) ← ClientUpdate(i, w_global)
          IF ||Δ_i||₂ > clip_norm THEN
            Δ_i ← Δ_i × (clip_norm / ||Δ_i||₂)
          ENDIF
          Add (Δ_i, n_i, q_i) to Uploads
        END
      Compute total_weight = Σ_i (n_i × max(q_i, ε))
      FOR each tuple (Δ_i, n_i, q_i) ∈ Uploads DO
        α_i = (n_i × max(q_i, ε)) / total_weight
      END
      Compute aggregated delta:
        Δ_global = Σ_i (α_i × Δ_i)
      Update server momentum:
        v = β × v + (1 - β) × Δ_global
      Update global model:
        w_global = w_global + lr_server × v
    END
  END FOR
  Return final global model w_global
END
-------------------------------------------------------------
Subroutine: ClientUpdate(i, w_server)
-------------------------------------------------------------
BEGIN
  Load local dataset D_orig (≈ 5000 images)
  D_paint ← PaintData(D_orig, prob_style=0.3, prob_stroke=0.4)
  D_mix ← MixDatasets(D_orig, D_paint, α_paint=0.4)
  Split D_mix → D_train (90%), D_val (10%)
  Set local model weights w_local ← w_server

  FOR epoch = 1 TO 3 DO
    FOR each minibatch (x, y) ∈ D_train of size 32 DO
      Compute loss:
```

```
          L = CE(f(w_local, x), y) + (μ/2) × ||w_local - w_server||₂²
        Compute gradient:
          g = ∇L(w_local)
        Update local model:
          w_local ← w_local - η × g
      END FOR
   END FOR

   Compute local update:
      Δ_i = w_local - w_server
   Evaluate model on D_val to compute validation loss L_val
   Compute quality metric:
      q_i = 1 / (L_val + ε)

   RETURN (Δ_i, |D_orig|, q_i)
END
---------------------------------------------------------------
Subroutine: PaintData(D_orig, prob_style, prob_stroke)
---------------------------------------------------------------
BEGIN
   Initialize D_paint = { }
   FOR each sample (x, y) ∈ D_orig DO
      x_p ← x
      IF random() < prob_style THEN
         x_p ← ApplyStyleTransfer(x_p, strength=0.6)
      ENDIF
      IF random() < prob_stroke THEN
         x_p ← AddRandomBrushStrokes(x_p, num_strokes=10, thickness=3)
      ENDIF
      Append (x_p, y) to D_paint
   END FOR
   RETURN D_paint
END
---------------------------------------------------------------
Subroutine: MixDatasets(D_orig, D_paint, α_paint)
---------------------------------------------------------------
BEGIN
   N = |D_orig| = 5000
   N_paint = int(α_paint × N) = 2000
   N_orig = N - N_paint = 3000
   D_mix = RandomSample(D_orig, N_orig) ∪ RandomSample(D_paint, N_paint)
   RETURN D_mix
END
```

4 Outcome of the research

The experimental setup, research outcome with visual analyses, evaluation metrics descriptions, and performance analysis comparing PTB-MFA with current models utilizing CTR, user engagement, precision, NDCG, and MAP values are all included in the result section. A system with an Intel Core i7 processor (3.4 GHz), 16 GB RAM, and NVIDIA GeForce RTX 3060 GPU (12 GB VRAM) was used for the experiment. Python 3.10, PyTorch 2.2, PySyft 0.8, and DGL 1.1 frameworks were used to create the model. Every experiment was conducted using federated nodes simulated on virtual clients and Windows 11 (64-bit).

4.1 Result outcomes

Figure 2 depicts the visualizations of a pie chart illustrating the distribution of product categories is shown in Figure 2 (a), with a balanced distribution across divisions such as sports, books, and clothing. An Area Chart of local model correctness is shown in Figure 2 (b), which shows constant learning performance. A product price histogram with a uniform distribution is shown in Figure 2 (c). A heatmap in Figure 2 (d) illustrates the substantial relationships between important characteristics determining tailored recommendations.

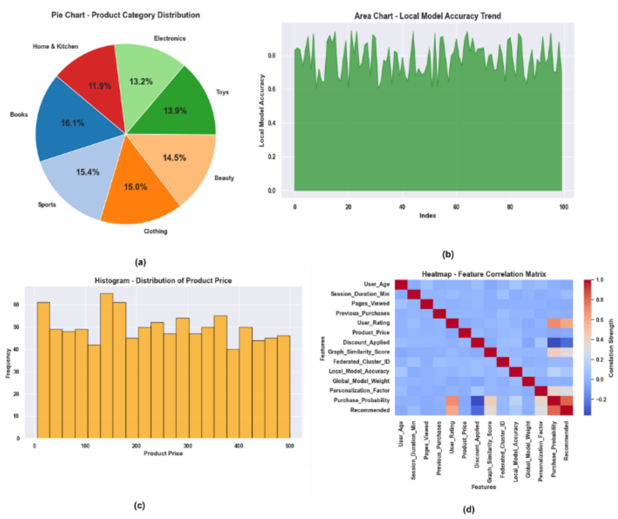

Figure 2: Feature distribution visualization of (a) product category distribution (b) local model accuracy trend (c) distribution of product price and (d) feature correlation matrix

Figure 3 demonstrates the illustrations of the Knowledge Graph structure that links users, goods, brands, and categories to capture semantic relationships for tailored recommendations is shown in Figure 3 (a). The application of KDE user age distribution as shown in Figure 3 (b), in order to demonstrate how engagement is distributed across user age. Figure 3 (c) shows a Candlestick Chart of pages visited over time, with regard to a change in browsing behavior. To bring some clarity to the purchasing behavior over time, Figure 3 (d) shows the Time-Series Decomposition of past purchases into its components of trend, seasonality, and residual.

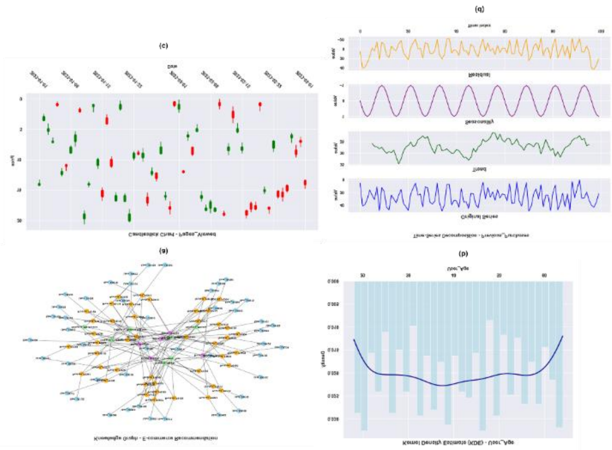

Figure 3: Exploratory data and behavioral analysis of (a) knowledge graph (b) KDE of user age (C) candlestick chart of pages viewed and (d) time series decomposition

4.1.2 Ablation study and computational overhead analysis

To quantify the contribution of Painting Training-Based Optimization (PTB) within the proposed framework, an ablation study was conducted by comparing PTB-MFA with a baseline Federated Averaging (FedAvg) model using identical network architecture, dataset partitions, and training rounds. The comparison isolates the impact of PTB on personalization accuracy and convergence behavior.

Results indicate that replacing standard FedAvg with PTB-based optimization improves CTR by approximately 2.8% and MAP by 1.9%, demonstrating that PTB contributes substantially to client-level personalization beyond global aggregation alone. Additionally, PTB-MFA exhibits faster convergence within fewer communication rounds, reducing overall training instability.

In terms of computational overhead, PTB introduces a marginal increase in local client computation due to optimization updates; however, this overhead remains acceptable for real-world deployment, as no raw data exchange occurs and communication costs remain comparable to standard federated learning approaches.

4.2 Evaluation metrics

CTR - CTR represents the percentage of users that click on a suggested item over the total possible presentations of that item. CTR is an important measure of both suggestion relevance and engagement efficacy, representing user interest and the ability of the system to store interest.

User-Engagement- User engagement refers to the extent to which users actively interact with the technology by means of clicks, views, transactions, or time. In an e-commerce environment, it reflects the system's ability to capture shopper's attention, representing overall satisfaction and trust in the recommendation process.

Precision-By evaluating the ratio of pertinent items that are appropriately advised to the total number of recommended items, precision assesses the correctness of recommendations. In e-commerce, a high accuracy score reduces irrelevant recommendations and increases customer satisfaction by indicating that the majority of suggested products match user preferences.

NDCG-The relevancy and placement of items in the suggestion list are taken into account by NDCG when assessing the position and quality of recommendations. Relevant items with higher rankings add greater value to the score. Relevant products display early when the NDCG value is high, improving consumer happiness and suggestion efficacy.

MAP- MAP assesses ordering reliability by summing accuracy scores at each relevant item location for all users. It highlights the speed that appropriate products appear and indicates both relevancy and ranking order. Superior overall ability in providing precise, highly ranked individualized recommendations is indicated by a higher MAP.

4.3. Performance analysis

The proposed PTB-MFA method is compared with the existing DeepFM [23], KGAT [23], SASRec [23], CDARS [23], KG-BPR [24], BPR [24], NMF [24] SVD [24], KG-NN [24] and NLP [24].

Table 3 and Figure 4 compare PTB-MFA's performance metrics to those of other methods. PTB-MFA achieved the greatest CTR (16.9%), user engagement (19.9%), accuracy (0.778), and NDCG (0.987), demonstrating greater personalization and engagement efficacy.

Table 3: Performance evaluation of proposed and the exiting.

Methods	**CTR (%)**	**User Engagement (%)**	**Precision**	**NDCG**
DeepFM [23]	10.8 %	12.2%	0.432	0.538
KGAT [23]	12.1 %	14.5%	0.448	0.561
SASRec [23]	13.6 %	15.4%	0.471	0.574
CDARS [23]	14.7 %	16.7%	0.496	0.599
PTB-MFA [Proposed]	16.9 %	19.9%	0.778	0.987

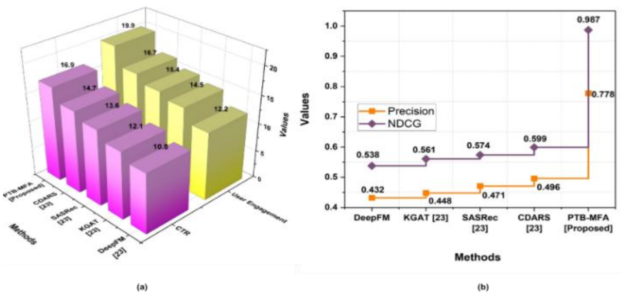

Figure 4: Comparison of Existing and Proposed Methods Based on (a) CTR, User Engagement and (b) Precision, and NDCG Metric

The proposed PTB-MFA model achieves the highest MAP score of 6.37% in the Table 4 and Figure 5 that compare MAP performance, greatly outperforming existing recommendation models.

Table 4: Comparison of MAP (%) values.

Methods	MAP (%)
KG-BPR [24]	4.81%
BPR [24]	4.5%
NMF [24]	4.39%
SVD [24]	2.95%
PTB-MFA [Proposed]	6.37%

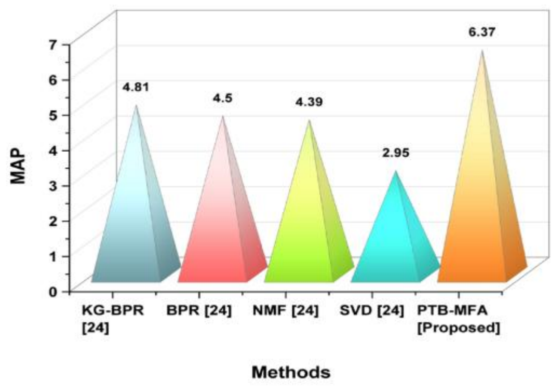

Figure 5: Visualization of MAP metric for proposed and existing.

The proposed PTB-MFA outperforms all existing techniques with the highest precision of 23.6%, according to Table 5 and Figure 6 that compare the precision scores of several models.

Table 5: Outcome of existing and proposed for precision

Methods	Precision (%)
KG-NN [24]	21.3%
MLP [24]	11.6%
NMF [24]	11.5%
SVD [24]	4.69%
PTB-MFA [Proposed]	23.6%

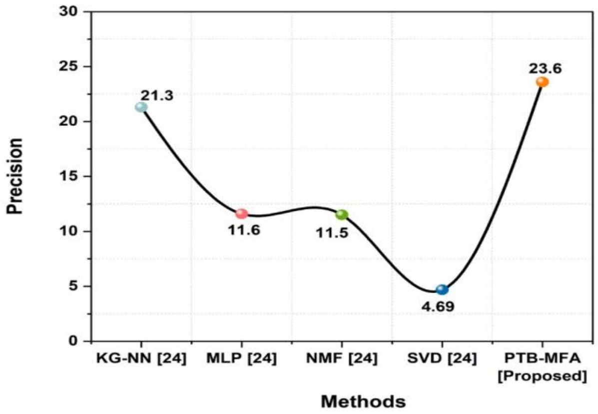

Figure 6: Precision comparison of existing and proposed methods.

4.5 Discussion

From a systems perspective, the proposed PTB-MFA framework shares conceptual similarities with adaptive and robust control strategies used in dynamic multi-agent systems. Similar to nonlinear optimal control and neural network-based adaptive control methods used in dynamic multi-agent systems [26–28], the proposed approach dynamically adjusts local model parameters to handle heterogeneous and time-varying user behaviors across distributed clients.Unlike classical control techniques that rely on explicit mathematical system models, PTB-MFA achieves adaptive optimization through data-driven learning while maintaining global stability via federated aggregation. This design enables effective handling of uncertainty and evolving user preferences in large-scale e-commerce environments. In real-world deployment scenarios, PTB-MFA addresses key challenges such as latency, data heterogeneity, and privacy compliance. By performing optimization locally and sharing only encrypted parameter updates, the framework complies with data protection regulations while supporting heterogeneous client devices. Although federated aggregation may introduce communication latency, this trade-off is justified by enhanced privacy preservation and personalization accuracy in large-scale e-commerce systems. Related adaptive and flatness-based control strategies applied in autonomous vehicles and robotic manipulators further support the relevance of adaptive optimization principles in distributed learning environments [29–31].

Compared with existing models such as DeepFM [23] and KGAT [23], the proposed PTB-MFA framework achieves higher CTR and MAP values by jointly optimizing semantic representation and client-level personalization under privacy constraints.

5 Conclusion

The research forms a highly individualized, knowledge conscious, privacy conscious recommendation system, which is capable of supporting a broad spectrum of user preferences. The suggested PTB-MFA approach integrates federated learning with a metaheuristic optimization strategy to enhance the personalization of clients on a case-by-case basis and use global trends. The proposed method has a better CTR (16.9%), User Engagement (19.9%), and MAP (6.37) in comparison to the existing methods and proves to be more personal and accurate in e-commerce recommendations. The research is faced with challenges associated with delays in communication during federated aggregation when using large-scale heterogeneous data. It is important to note that the proposed framework is evaluated on a medium-scale public dataset, and real-world deployment may introduce additional challenges related to communication delays, device heterogeneity, and large-scale client participation. These limitations suggest that the reported results should be interpreted as indicative rather than definitive. Future directions will be focused on enhancing real-time adaptability, achieving higher compute effectiveness and scaling to more accurate and privacy-sensitive personalized e-commerce suggestions.

Declarations

Ethics approval and consent to participate: I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

Consent for publication: I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

Availability of data and materials: The data used to support the findings of this study are available from the corresponding author upon request.

Competing interests: Here are no have no conflicts of interest to declare.

All authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

Authors' contributions (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript.

There is no human participate involved in this research. this article manuscript is created from collection of data set.

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Abbreviation	Fullform
EC	E-Commerce
GAs	Genetic algorithms
SVR	Support Vector Regression
DSS	Decision Support System
PTB-MFA	Painting Training-Based Optimization with Modified Federated Averaging
DL	Deep Learning
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
VGG-Net	Visual Geometry Group Network
RF	Random forest
GBDT	Gradient Boosting Decision Tree
ML	machine learning
AI	artificial intelligence
LightGBM	Light Gradient Boosting Machine
DNN	Deep Neural Network
MCDM	multi-criteria decision-making
COCOSO	Combined Compromise Solution

EDAS	Evaluation based on Distance from Average Solution
MAIRCA	MultiAttributive Ideal-Real Comparative Analysis
MABAC	Multi-Attributive Border Approximation Area Comparison
CRITIC	CRiteria Importance Through Intercriteria Correlation
ConvLSTM	Convolutional Long-Short Term Memory
PTBO	Painting Training-Based Optimization
MFA	Modified Federated Averaging
KGE	Knowledge Graph Embedding
PCA	**Principal component analysis**
PTBO	Painting Training-Based Optimization
CTR	Click-Through Rate
NDCG	Normalized Discounted Cumulative Gain
MAP	Mean Average Precision
KDE	Kernel Density Estimate
DeepFM	Deep Factorization Machine
KGAT	Knowledge Graph Attention Network
SASRec	Self-Attentive Sequential Recommendation
CDARS	Collaborative Deep Attention Recommendation System
KG-BPR	Knowledge Graph–Based Bayesian Personalized Ranking
BPR	Bayesian Personalized Ranking
NMF	Non-negative Matrix Factorization
SVD	Singular Value Decomposition
KG-NN	Knowledge Graph–Based Neural Network
NLP	Neural Language Processing