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A Privacy-Preserving Book Recommendation System for Electronic Libraries Using Federated Neural Collaborative Filtering

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Abstract

The rapid increase in digital resources for electronic library systems has necessitated intelligent recommendation mechanisms that can help users discover relevant academic materials promptly and efficiently. Traditional recommendation systems are often based on centralized machine learning approaches that collect and store users' interaction data on a central server, thereby raising concerns regarding privacy, data security, and regulatory compliance. This study presents a Federated Learning-Based Book Prediction and Recommendation System for Electronic Library Environments. The proposed framework employs a privacy-preserving distributed learning architecture in which user reading histories, ratings, search activities, and borrowing patterns remain on local devices, but only model parameters are shared with a central aggregation server. A Neural Collaborative Filtering (NCF) model is adopted to learn user preferences and book characteristics, and the Federated Averaging (FedAvg) algorithm is utilized to aggregate locally trained models into a global recommendation model. An electronic library dataset comprising 5,000 users, 1,000 books, and over 200,000 user-book interactions was generated to simulate realistic library usage. The dataset was preprocessed and distributed among twenty federated clients for decentralized model training. The simulation was carried out using Python and PyTorch, while SQLite was employed for local data management, and Tkinter was used to develop a graphical user interface for the prototype application. Performance evaluation demonstrated that the proposed federated recommendation model achieved an accuracy of 92.84%, precision of 91.63%, recall of 90.78%, and F1-score of 91.20%. The study demonstrates that Federated

Learning provides an effective framework for developing privacy-preserving recommendation systems capable of delivering accurate and personalized book recommendations in electronic library environments.

Keywords: Federated Learning, Electronic Library System, Book Recommendation, Neural Collaborative Filtering, Privacy-Preserving Machine Learning, Federated Averaging.

Introduction

Electronic libraries provide remote access to digital books, journals, conference papers, and other intellectual materials. The electronic library systems, or E-Libraries, have become a crucial part of contemporary educational establishments (Wang & Wang, 2024). As the volume of digital content continues to grow, users often struggle to find the most relevant books and learning materials that align with their interests and academic needs (Daimari et al., 2023). Traditional recommendation systems use centralized machine learning approaches, which require collecting user ratings, search logs, reading histories, and borrowing information on a central server (Yan et al., 2026). While such methods can provide accurate recommendations, they introduce significant privacy concerns because sensitive user data is stored and processed in a centralized location (Patil & Kanade, 2025). Unauthorized access, data breaches, and privacy violations can negatively affect users' trust in electronic library services (Abdelrahman, 2026; Asad et al., 2023). Most existing electronic library recommendation systems use centralized architectures that collect and store user data on a central server for model training.

The classical approach presents several challenges: (1) privacy risks associated with centralized storage of user reading histories; (2) increased vulnerability to cyberattacks and data breaches; (3) poor personalization due to insufficient utilization of distributed user behaviour patterns; (4) limited trust among users regarding how their personal information is used; (5) compliance challenges with data protection regulations. Therefore, a recommendation framework is needed that can generate accurate book recommendations while preserving user privacy and minimizing data exposure (Ali et al., 2021; Imran et al., 2022). Federated Learning (FL) has emerged as a privacy-preserving machine learning paradigm that enables multiple devices or institutions to collaboratively train a machine learning model without sharing raw user data (Yan et al., 2026). Instead, the central aggregation server and participants only share updates or model parameters. This approach preserves the quality of suggestions while improving user privacy (Garst et al., 2025). Thus, this study proposes the design and implementation of a Federated Learning-based Book Prediction and Recommendation System for Electronic Libraries.

The study aims to develop and evaluate a privacy-preserving book recommendation system for electronic libraries by integrating Neural Collaborative Filtering with Federated Learning using the Federated Averaging algorithm. The specific objectives are to:

i. design a book recommendation framework that integrates Neural Collaborative Filtering and Federated Learning for electronic library environments.
ii. develop a federated recommendation model that uses local model training and Federated Averaging to aggregate model updates from simulated electronic library clients.

iii. evaluate the recommendation performance of the proposed system using accuracy, precision, recall, and F1-score.

To achieve these objectives, three appropriate research questions were formulated to guide this study. These research questions are:

1. How can Neural Collaborative Filtering (NCF) be integrated with Federated Learning (FL) to develop a privacy-preserving book recommendation system for electronic libraries?
2. To what extent does the proposed Federated Averaging (FedAvg) approach improve the accuracy of book recommendations compared with a conventional centralized NCF model?
3. How does the proposed federated recommendation system perform in terms of accuracy, precision, recall, and F1-score?

Answering these questions will enable the study to achieve its aim and objectives. This study contributes to knowledge by developing a privacy-preserving book recommendation framework for electronic library systems that integrates Neural Collaborative Filtering (NCF) with Federated Learning using the Federated Averaging (FedAvg) algorithm. The study combines deep learning-based preference prediction with decentralized model training to support personalized book recommendations while reducing direct exposure of users' reading histories and ratings. It extends federated recommendation beyond commonly studied domains, such as movies and e-commerce, to electronic library environments. The study also evaluates the proposed model using a simulated electronic library dataset and the performance metrics of Accuracy, Precision, Recall, and F1-Score, providing an empirical basis for assessing its recommendation capability.

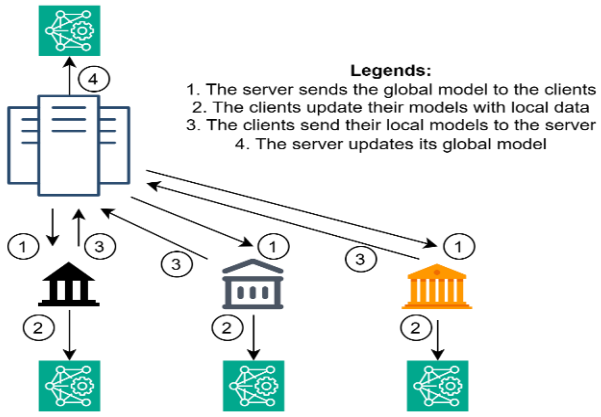


Figure 1: The FedAvg Framework (Adapted from Li et al., 2022).

As shown in Figure 1, the FedAvg framework presents an implementable architecture in which simulated clients train locally and share model updates with the server for global aggregation, providing a foundation for future deployment across multiple libraries or educational institutions. The rest of the paper is organized as follows: related work is provided in Section 2; the materials and methods employed in this study are given in Section 3; the results and discussions are presented in Section 4; and Section 5 concludes the paper with relevant references.

Related Work

The rapid digitization of educational resources has transformed traditional libraries into electronic library (e-library) systems capable of providing users with instant access to a vast collection of digital

books, journals, theses, and multimedia resources. However, the exponential growth in available digital content has introduced the challenge of information overload, making it increasingly difficult for users to identify relevant learning materials efficiently (Ahmad et al., 2025; DRISYA, 2025). To address this challenge, intelligent recommendation systems have become an essential component of modern e-library platforms. Recommendation systems employ machine learning techniques to analyse users' preferences, reading histories, search patterns, and ratings to predict resources that align with individual interests.

Conventional recommendation systems predominantly utilize centralized learning architectures, where user interaction data are collected and processed on a central server. While these systems often achieve satisfactory recommendation accuracy, they expose users to significant privacy and security risks due to the centralized storage of sensitive information (McMahan et al., 2017). The emergence of Federated Learning (FL) has provided an alternative paradigm for developing privacy-preserving recommendation systems. Federated learning enables distributed devices to collaboratively train machine learning models without sharing raw user data. Instead, devices transmit only model parameters to a central aggregation server, reducing the risk of privacy leakage while maintaining predictive performance.

Federated Learning (FL) is a decentralized machine learning approach. As introduced by McMahan et al. (2017), FL is an approach that allows clients to locally aggregate their computed updates without allowing their training data to be shared globally. FL has found applications in several domains (Shaheen et al., 2022). In healthcare, it can be used to emulate medical procedures (Danish Javeed et al., 2024), and in other areas such as smart cities, industrial IoT, medical internet of things (MIoT), and educational settings (Ayeelyan et al., 2024; Kochon et al., 2024). Several researchers have proposed intelligent recommendation systems for educational and digital library environments. Early systems primarily employed collaborative filtering and matrix factorization techniques (Daimari et al., 2023; Peña et al., 2020) to recommend books based on borrowing histories and user ratings. Subsequent studies introduced deep learning models capable of capturing complex user-item relationships and improving recommendation accuracy.

More recent investigations have incorporated federated learning into recommendation systems to preserve user privacy (Ali et al., 2021; Yan et al., 2026). These studies reported competitive prediction performance while significantly reducing the exposure of sensitive user data. FL is further enhanced with the use of Neural Collaborative Filtering (NCF), a deep learning paradigm for recommender systems that uses a neural network architecture, which generalises matrix factorization and can learn complex, non-linear user-item interactions and arbitrary functions from data (He et al., 2017). However, many existing implementations concentrate on commercial domains such as movie recommendation, e-commerce, and music streaming, with comparatively limited attention given to electronic library systems (Ali et al., 2021; Ravikumar & Aarthi, 2025; Yan et al., 2026). Hence, the current study intends to fill this gap.

Materials and Methods

The work proposes a recommendation system for an electronic library system using federated neural collaborative filtering based on research by He et al. (2017). This section describes the research design, system architecture, dataset generation, and algorithms for the simulation and evaluation employed to assess the performance of the proposed system. The methodology combines software engineering principles with machine learning techniques to develop, test, and evaluate a privacy-preserving recommendation framework.

System Architecture

The proposed system follows a federated client-server architecture that consists of five major components: the user interaction layer, the local training layer, the federated learning server, the global model aggregation, and the recommendation engine. Figure 2 shows the interaction of each of these modules.

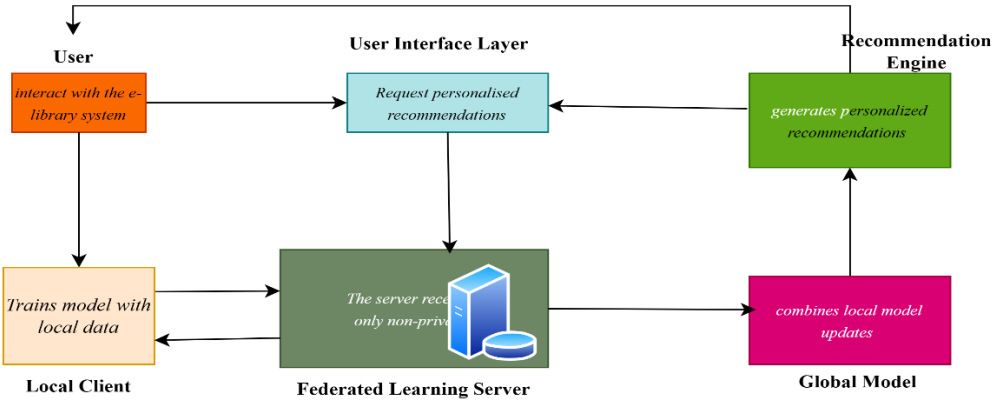


Figure 2: Proposed Federated Learning Model Architecture

User Interaction Layer: - This is where the user interacts with the system through book searches, downloads, book ratings, reviews, borrowing activities, and reading duration. Meanwhile, the generated data remains on local devices and is not globally accessible.

The Client Training Layer: - This is a layer where each user device (Client) trains a local recommendation model using reading history, search patterns, ratings, and book categories, using global updates from the server. Again, the local data never leaves the user's device.

The Federated Learning Server: - The central server receives only the model weights, gradient updates, and training parameters, but does not receive the user identities, reading records, and personal information.

The Global Model Aggregation: - The server combines local model updates using the Federated Averaging (FedAvg) algorithm. The server aggregates local model parameters using the formula:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{N} w_k \quad (1)$$

Where:

w_{t+1}= Updated global model

w_k= Local model parameters

n_k= Number of local samples

N= Total samples

K= Number of participating clients.

Using Equation 1, the server aggregates the local model parameters without exposing privacy data, as shown in Algorithm 1:

Algorithm 1: Federated Averaging (FedAvg)

Input:

Local Model

Number of Clients

Output:

Global Model

Initialise Global Model

For each round:

Send Global Model to Clients

For each Client:

Train Local Model

Send Updated Weights

Aggregate Weights

Update Global Model

Return Global Model

Thus, the methodology ensures privacy preservation, reduced communication overhead, and scalability.

Recommendation Engine: - The trained global model at this layer predicts top-N books, user interests, and similar books. The Neural Collaborative Filtering (NCF) algorithm, a deep learning framework that delivers personalized product or content recommendations by replacing the traditional linear inner product in Matrix Factorization with neural networks, is used in this module.

Algorithm 2: Neural Collaborative Filtering (NCF)

Input:

User Features

Book Features

Output:

Recommendation Score

Embed Users

Embed Books

Concatenate Features

Feed into Neural Network

Rank Books

Return Top-N Recommendations

Proposed System Simulation and Evaluation

The proposed system was implemented and simulated in Python using PyTorch for deep learning and Neural Collaborative Filtering (NCF) as the recommendation model. Federated learning was implemented using the Federated Averaging (FedAvg) algorithm, with all modules implemented for demonstration. The FedAvg algorithm was used to aggregate local model parameters or updates, using a weighted average based on the number of training examples at each client.

Data Description

The electronic library dataset used in this work was simulated based on a Library Transaction Dataset that tracks user borrowing records, overdue statuses, and interactions for building prediction models (Ziya, 2025). Each record in the dataset represents an individual transaction where a user interacts with a library's catalogue, either by borrowing or reserving a book. The dataset contains the following key features:

User ID: A unique identifier for each user, representing students, faculty, or staff.
Book ID: A unique identifier for each book in the library.
Borrow Date: The date when a book was borrowed by the users.
Return Date: The date when the book was returned to the library.
Reservation Status: A binary value indicating whether the book was reserved by the user before borrowing.
Overdue Status: The target variable, indicating whether the book was returned after the due date (1 for overdue, 0 for not overdue).
User Role: The role of the user within the library system (e.g., student, faculty, or staff).
Book Category: The category or genre of the book (e.g., fiction, non-fiction, science, history, art).
The performance metrics are used to evaluate the dataset, and the results are presented in the next Section. The experimental configuration is as shown in Table 1:

Table 1: Experimental Configuration

Variable	Value
Number of Users	5,000
Number of Books	1,000
User-Book Interactions	218,547
Federated Clients	20
Communication Rounds	50
Local Training Epochs	5
Batch Size	64
Learning Rate	0.001
Embedding Dimension	32
Training/Test Split	80% / 20%

Following Li et al. (2022), the partitioning strategies used in the study were based on non-independently and identically distributed (i.e., non-IID) data distributions. This is at the user level, given non-IID partitioning that combines user allocation, transaction-volume imbalance, and a Dirichlet-based preference distribution. This approach is more realistic than randomly distributing all transactions equally because actual electronic libraries differ in the number of active users, transaction volumes, and book-category preferences. The non-IID partitioning strategy combines these three forms of heterogeneity, in which clients receive different numbers of users and transactions, have different proportions of book categories, such as science, engineering, agriculture, management, and social sciences, etc., and contain different patterns of reading and borrowing activity, including frequent readers, occasional readers, and users with specialised interests. Thus, the Dirichlet distribution was used to generate different category proportions for each client based on:

$$\pi_k \sim Dirichlet\ (\alpha\beta) \tag{2}$$

Where:
π_k represents the category distribution of client k.
β represents the overall category proportions in the dataset.
α controls the degree of heterogeneity.
It should be noted that a smaller α produces more heterogeneous client distributions, while a larger α produces more similar distributions. For instance, if the first client initially receives seven thousand five hundred (7,500) transactions with two hundred (200) users, the average transactions per user will be

thirty-seven and a half (37.5). In the experimental setting, $\alpha = 0.3$ was used in this work, which accounts for all 5,000 users and all 218,547 transactions in a stable allocation.

Performance Metrics

The performance metrics include recommendation accuracy, precision, recall, and F1 score.

Recommendation Accuracy: This measures the overall correctness of the system across all items (both liked and disliked). It calculates the proportion of correct recommendations out of total predictions. It is given as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Precision: This measures the quality of the recommended list and is vital when false positives (bad recommendations) are highly annoying to the user; that is, the relevance of recommended books. The precision is as follows:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

Recall: This measures the system's completeness, ensuring the user doesn't miss out on relevant content, even if a few less relevant items sneak in, that is, retrieval effectiveness. It is given as:

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

F1 Score: This is the harmonic mean of Precision and Recall. It provides a single score that balances both metrics, which is especially helpful when you need to keep both the quality and completeness of recommendations in check.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

Equations 3 to 6 are applied to the data collected for analysis after the data cleaning exercise, and the results are presented in the next Section.

Results and Discussion

Results:- The proposed recommendation system's performance was evaluated using standard machine learning metrics, and the results obtained are as follows:

Table 2. Performance Metric Results

S/N	Metric	Value
1.	Accuracy	92.84%
2.	Precision	91.63%
3.	Recall	90.78%
4.	F1-Score	91.20%

The performance metric results are 92.84% for recommendation accuracy, 91.63% for precision, 90.78% for recall, and 91.20% for F1 score. The results demonstrate that the proposed federated recommendation system achieved high predictive performance. The high accuracy, precision, and recall indicate that the model effectively identified books relevant to individual users while minimizing false recommendations. To evaluate the effectiveness of the proposed federated learning approach, its performance was compared with a conventional centralized recommendation model using the bar chart presented in Figure 3.

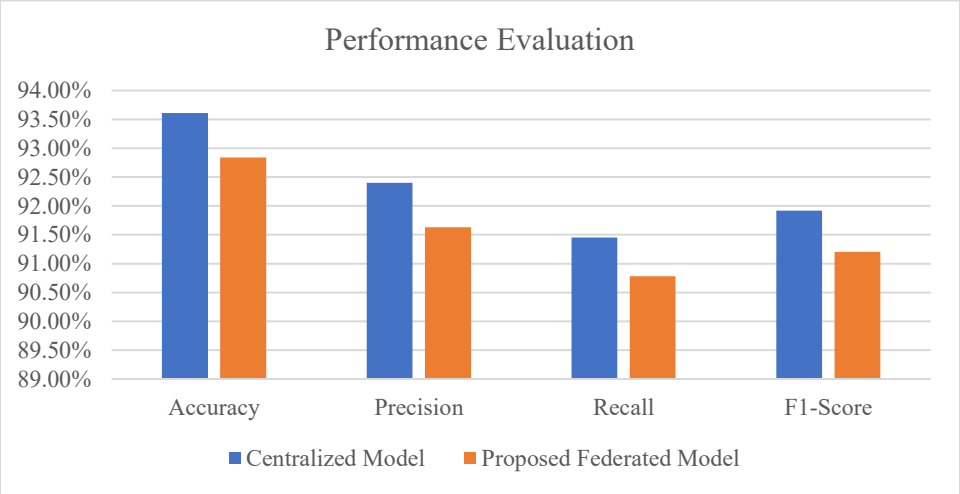


Figure 3: Performance Comparison of Centralized and Federated Models

Figure 3 shows that the centralized model achieved slightly higher predictive accuracy; the difference was less than one percentage point. In contrast, the proposed federated model significantly enhanced user privacy by ensuring that sensitive reading histories remained on local devices. Unlike centralized recommendation systems that transmit complete user interaction histories to a remote server, the proposed system transmitted only encrypted model parameters. These results are benchmarked against recent studies by Ali et al. (2021) and Yan et al. (2026). It should be noted that the federated learning approach proposed in Ali et al. (2021) was a context-aware recommender system in federated cars (Fed-cars), while Yan et al. (2026) adopted this methodology in heterogeneous financial environments.

Table 3: Comparison of Results

Study (Model)	Accuracy	Precision	Recall	F1 Score
Yan et al., 2026	89.7% (Approx. 90%/	87.3%	89.7%	88.5%
Proposed Study	92.84%	91.63%	90.78%	91.20%

From the results obtained in the proposed study, it can be seen that the difference between the traditional centralised system and the use of the federated model for all the performance metrics was not up to a unit. So, it can be deduced that the proposed study outperformed the study under comparison. This study's precision is 4 units, and recall is over 2.5 units higher than those obtained by Yan et al. (2026). This is significant because they show whether the recommendation system is both useful and balanced. However, these results cannot be directly compared with those of Ali et al. (2021) because they reported only the mean absolute error (MAE), root mean squared error (RMSE), and normalized discounted cumulative gain (nDCG), which are not the primary concerns of the current study. Meanwhile, the proposed system recorded an F1-score of 91.20%, which indicates balanced classification. Ali et al. (2021) obtained the nDCG values of 84.92% and 64.59%, respectively. Hence, the F1-score measures classification performance, whereas nDCG measures the quality of the ordering of recommended items.

Discussion

The accuracy, precision, recall, and F1-score of the proposed privacy-preserving book recommendation system were 92.84%, 91.63%, 90.78%, and 91.20%, respectively. These findings suggest that under experimental conditions, the Neural Collaborative Filtering (NCF) model combined with Federated Averaging (FedAvg) exhibits promising recommendation performance. That is, the model accurately classified about 93 out of every 100 examined suggestion instances, according to the recommendation accuracy of 92.84%. This shows that it can appropriately differentiate between book recommendations that are relevant and those that are not.

Also, the precision of 91.63% indicates that about 92 out of every 100 books that were recommended as relevant were, in fact, relevant according to the study's performance evaluation. This suggests that the system has a relatively low rate of irrelevant recommendations, which is important for improving users' experiences in electronic libraries. Similarly, the recall of 90.78% indicates that the system successfully identified approximately 91 out of every 100 books classified as relevant in the test dataset. This demonstrates its ability to retrieve relevant books, although some relevant titles may still be overlooked. The F1-score of 91.20% represents the harmonic mean of precision and recall. It demonstrates a relatively balanced relationship between the system's ability to recommend relevant books and its ability to retrieve available relevant titles.

Overall, the findings support the adoption of federated learning as a practical solution for developing intelligent electronic library recommendation systems that balance recommendation quality with user privacy. The proposed framework is scalable, privacy-aware, and adaptable to institutional digital libraries, where protecting users' reading histories and interaction data is an important consideration.

Conclusion

In this study, a Federated Learning-based Book Prediction and Recommendation System for Electronic Library Systems was developed. The proposed system integrates Neural Collaborative Filtering (NCF) with the Federated Averaging (FedAvg) algorithm to enable collaborative model training across multiple clients without transferring users' raw interaction data to a central server. Instead, only locally trained model parameters are communicated to the aggregation server, thereby preserving the confidentiality of user information.

An electronic library dataset comprising 5,000 users, 1,000 books, and over 200,000 user-book interactions was generated to simulate realistic library usage. The dataset was pre-processed and distributed among twenty federated clients for decentralized model training. The simulation was carried out using Python and PyTorch, while SQLite was employed for local data management, and Tkinter was used to develop a graphical user interface for the prototype application.

Performance evaluation demonstrated that the proposed federated recommendation model achieved an accuracy of 92.84%, precision of 91.63%, recall of 90.78%, and F1-score of 91.20%. The study demonstrates that Federated Learning provides an effective framework for developing privacy-preserving recommendation systems capable of delivering accurate and personalized book recommendations in electronic library environments. Although the proposed Federated Learning-based Book Prediction and Recommendation System demonstrated promising performance in terms of recommendation accuracy, scalability, and privacy preservation, several opportunities exist for extending and improving the framework.

On the flip side, this study has three identified limitations. First, the use of synthetic or simulated client data distributions may not adequately represent the diversity of user behaviours, reading preferences, and data heterogeneity found in actual institutional electronic libraries, thereby limiting the

generalisability of the findings. Second, the absence of real-world testing on mobile and edge devices means that the system's performance under practical constraints such as limited processing power, memory capacity, battery life, and network connectivity remains unverified. Third, although FL reduces the need to centralise raw user-interaction data, the absence of formal Differential Privacy guarantees on shared model weights and updates leaves potential exposure to membership inference and model inversion attacks.

In future research, we intend to validate the system using real institutional datasets, conduct experiments on resource-constrained devices, and integrate differential privacy and secure aggregation to strengthen its privacy protection. Evaluating the system under real user interaction patterns would provide deeper insights into its practical effectiveness, generalisability, and overcome these identified limitations.

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