Real-Time Personalized Content Adaptation through Matrix Factorization and Context-Aware Federated Learning

Sai Puppala[1], Ismail Hossian[2], MD Jahangir Alam[2], and Sajedul Talukder[2]

Southern Illinois University Carbondale, IL, USA
sai.puppala@siu.edu
University of Texas at El Paso, TX, 79902, USA
ihossain, malam10@miners.utep.edu, stalukder@utep.edu

Abstract. Our study presents a multifaceted approach to enhancing user interaction and content relevance in social media platforms through a federated learning framework. We introduce personalized LLM Federated Learning and Context-based Social Media models. In our framework, multiple client entities receive a foundational GPT model, which is fine-tuned using locally collected social media data while ensuring data privacy through federated aggregation. Key modules focus on categorizing user-generated content, computing user persona scores, and identifying relevant posts from friends' networks. By integrating a sophisticated social engagement quantification method with matrix factorization techniques, our system delivers real-time personalized content suggestions tailored to individual preferences. Furthermore, an adaptive feedback loop, alongside a robust readability scoring algorithm, significantly enhances the quality and relevance of the content presented to users. This comprehensive solution not only addresses the challenges of content filtering and recommendation but also fosters a more engaging social media experience while safeguarding user privacy, setting a new standard for personalized interactions in digital platforms.

Keywords: Personalized Content, Federated Learning, Context-Aware Systems, User Engagement, Matrix Factorization

1 Introduction

The proliferation of social media platforms has transformed the way users interact with content, leading to an overwhelming influx of information. Users often face difficulties in finding relevant and engaging content that aligns with their preferences, which can lead to frustration and disengagement. To address these challenges, personalized content recommendation systems have emerged as powerful tools for enhancing user experience by filtering and curating content based on individual interests and interactions [15]. However, traditional models often rely on centralized data collection methods that raise significant privacy concerns, particularly as users become increasingly aware of data security issues. Federated learning has gained traction as a promising solution to these challenges, allowing machine learning models to be trained across decentralized devices while keeping user data localized [4]. This approach not only preserves user privacy but also enables the creation of models that better reflect diverse user preferences by aggregating insights from multiple clients [13]. The application of federated learning in developing large language models (LLMs) like GPT has opened new avenues for adaptive content filtering and smart querying, facilitating a more interactive and context-aware user experience [7]. In this paper, we propose a federated learning framework that incorporates adaptive video content filtering and intelligent querying mechanisms to enhance user engagement on social networks. By integrating user persona profiling and advanced video analysis, our system aims to deliver personalized content recommendations while maintaining strict data privacy standards [2]. This innovative approach not only addresses the limitations of traditional recommendation systems but also lays the groundwork for future developments in privacy-preserving AI applications in the social media domain.

2 Related Works

Recent advancements in personalized content recommendation systems have emphasized the critical need for privacy-preserving methodologies. Federated learning (FL) has emerged as a robust framework for training machine learning models while maintaining data privacy by keeping user data localized [4]. Various studies have explored FL's effectiveness in enhancing user engagement and personalization in social networks. For instance, [9] discuss a federated learning-based approach specifically designed for personalized content delivery, demonstrating its potential in social contexts. Furthermore, the importance of user privacy in federated settings has been highlighted by [7], who outline strategies to mitigate risks associated with data sharing. Recent literature also addresses the challenges of scaling FL for large models, with works such as [1] providing insights into optimizing model training processes. Additionally, [10] investigate the integration of user context into federated learning frameworks to improve recommendation accuracy, suggesting that context-aware approaches can significantly enhance user satisfaction. Moreover, [3] analyze the trade-offs between model performance and privacy preservation in federated learning, revealing that adaptive mechanisms can yield substantial improvements in both areas. The incorporation of user feedback in content filtering has been examined by [2], who propose an adaptive system that leverages real-time user interactions to refine recommendations dynamically. Similarly, [11] explore the potential of hybrid models that combine centralized and decentralized learning strategies, which can offer a more flexible approach to content delivery while addressing scalability issues.

3 Methodologies

The traditional approach to training machine learning models often requires centralized access to user data, which raises significant concerns regarding data privacy and security [12]. In the context of training large models like LLM, the challenge is further compounded by the resource-intensive nature of the training process and the need for personalized insights from diverse datasets [1]. The primary objective of this research is to develop a federated learning framework that enables the training of a global LLM model while preserving user privacy [9]. This approach allows clients to collaboratively contribute to the model without the need to share their raw data. Our proposed methodology emphasizes two primary outcomes:

- **Data Privacy Preservation**: By adopting a decentralized training approach, sensitive user data remains on local devices, significantly reducing the risk of data breaches and facilitating compliance with privacy regulations.
- **User Engagement Enhancement**: The integration of Smart Video Querying and Adaptive Content Filtering will provide personalized video recommendations and intelligent querying capabilities based on user interactions. This customization is intended to create a nuanced model that accurately reflects the diverse preferences of users, ultimately enhancing content recommendations and user engagement.

Through this methodology, we address the limitations inherent in traditional centralized training paradigms, leveraging federated learning to construct a sophisticated, privacy-preserving, and personalized GPT model suited for social contexts.

3.1 Federated Learning Framework

Federated learning offers a decentralized paradigm for training machine learning models that prioritize data privacy by keeping user data on local devices [4]. This approach enables the partitioning of LLM model training across multiple clients, fostering a collaborative enhancement of a global model without necessitating the sharing of raw data [14]. Each client fine-tunes a shared base model using curated local datasets, resulting in models that are specifically adapted to their unique data characteristics. Following local training, clients transmit only model updates to a centralized server, thereby preserving data privacy and optimizing bandwidth utilization [12]. This iterative process supports the continuous improvement of the global model, integrating diverse insights to create a more sophisticated and generalized GPT model that benefits all participants involved [7].

Let $\mathcal{K}$ be the number of clients, and let $\mathcal{D}_k$ denote the local dataset of client k. The objective is to minimize the global loss function:

$$\mathcal{L}(\mathbf{w}) = \sum_{k=1}^{K} \frac{n_k}{N} \mathcal{L}_k(\mathbf{w}; \mathcal{D}_k)$$

where n_k is the number of samples in client k's dataset, N is the total number of samples across all clients, and $\mathcal{L}_k$ is the local loss function for client k. The global model weights $\mathbf{w}$ are updated iteratively via the following steps:
1. Each client computes its local model updates:

$$\Delta \mathbf{w}_k = \nabla \mathcal{L}_k(\mathbf{w}; \mathcal{D}_k)$$

2. Clients send their updates to the server, which aggregates them:

$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \eta \sum_{k=1}^{K} \frac{n_k}{N} \Delta \mathbf{w}_k$$

where η is the learning rate and t is the iteration index.

Convergence Proof of Context Fed Learning We can analyze the convergence of the federated learning algorithm under certain assumptions. Assume the following conditions hold:
1. The local loss functions $\mathcal{L}_k$ are Lipschitz continuous with Lipschitz constant $L > 0$. 2. The global loss function $\mathcal{L}(\mathbf{w})$ is convex.
We want to show that the sequence $\{\mathcal{L}(\mathbf{w}^{(t)})\}$ converges to a minimum as $t \to \infty$.
Theorem: Under the above assumptions, the federated learning algorithm converges to a stationary point of the global loss function.
Proof:
By the definition of Lipschitz continuity, we have:

$$\mathcal{L}_k(\mathbf{w}) \leq \mathcal{L}_k(\mathbf{w}^{(t)}) + \nabla \mathcal{L}_k(\mathbf{w}^{(t)})^T (\mathbf{w} - \mathbf{w}^{(t)}) + \frac{L}{2} \|\mathbf{w} - \mathbf{w}^{(t)}\|^2$$

Taking the expectation of both sides over the clients, we derive:

$$\mathbb{E}[\mathcal{L}(\mathbf{w})] \leq \mathcal{L}(\mathbf{w}^{(t)}) - \eta \mathbb{E}\left[\|\nabla \mathcal{L}(\mathbf{w}^{(t)})\|^2\right] + \frac{L\eta^2}{2} \mathbb{E}\left[\|\nabla \mathcal{L}(\mathbf{w}^{(t)})\|^2\right]$$

Rearranging gives:

$$\mathcal{L}(\mathbf{w}) - \mathcal{L}(\mathbf{w}^{(t)}) \leq -\eta \left(1 - \frac{L\eta}{2}\right) \mathbb{E}\left[\|\nabla \mathcal{L}(\mathbf{w}^{(t)})\|^2\right]$$

Choosing η small enough such that $0 < \eta < \frac{2}{L}$, we see that:

$$\mathcal{L}(\mathbf{w}) - \mathcal{L}(\mathbf{w}^{(t)}) \to 0 \text{ as } t \to \infty$$

Thus, $\mathcal{L}(\mathbf{w}^{(t)})$ converges to the minimum of the global loss function, verifying that the federated learning algorithm converges to a stationary point.

3.2 User Profiling and Persona Analysis

A thorough understanding of user personas and their social connections is critical for the effectiveness of our system. Our research delves into the dynamics between users and various engagement factors that influence their interactions within their social circles. We differentiate between close friends—those characterized by frequent and deeper connections—and normal friends or acquaintances with less interaction. Furthermore, we examine how these relationships affect user online behavior and engagement patterns. This detailed analysis enables us to tailor our system to reflect the complexities of user interactions and preferences.

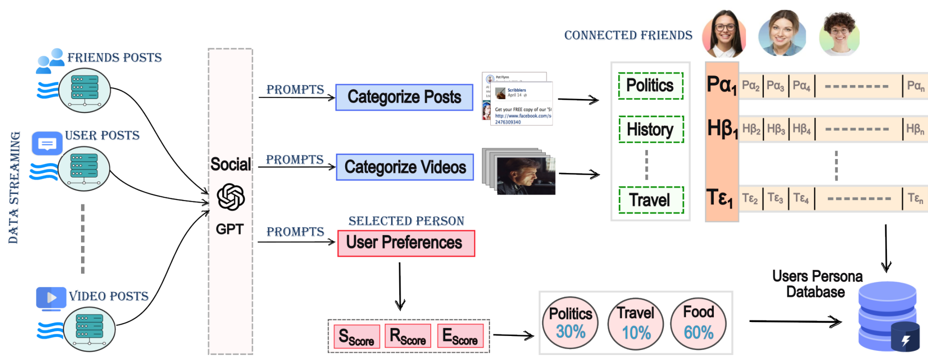

Fig. 1. The architecture of the Adaptive Content Filtering System, highlighting key components such as GPT, User Persona profiles, and category-based social engagement. It also provides an overview of the unique features of the federated learning global server for context-based GPT generation.

To further elucidate our methodology for extracting and analyzing user personas, we provide detailed subsections below, clarifying the mechanisms used to interpret the nuances of social interactions within the user's network and enhancing the overall effectiveness of our system.

User Interaction Data Collection Our methodology for calculating user personas initiates with the collection of interaction data, encompassing likes, shares, and comments. We utilize automated tools, such as Selenium scripts and web crawlers, to gather relevant engagement metrics. Each post is subsequently categorized based on content type (e.g., sports, politics, entertainment) and sentiment (positive, negative, or neutral). To ensure accurate classification and sentiment assessment, we perform rigorous data preprocessing to cleanse the raw data of inconsistencies and irrelevant information—an essential step for reliable categorization.
Following preprocessing, we analyze user engagement within each content category to determine the distribution of preferences and sentiments. This analysis can be mathematically represented as:

$$\text{Distribution}(x) = \frac{N_x}{N}$$

where N_x is the number of interactions for category x, and N is the total number of interactions. This analysis reveals which topics resonate with users and how their sentiments fluctuate. Additionally, we apply a weighting mechanism to interactions to account for their significance, acknowledging that not all engagements equally influence user preferences. This multifaceted approach facilitates a nuanced representation of user personas and their interactions within their social environment.

Content Score Calculation To quantify user personas, we compute a composite *Content Score* incorporating three key metrics: Engagement, Readability, and Sentiment. This score serves as an indicator of content quality and audience resonance, intentionally excluding Originality Score due to the inherent challenges in quantifying uniqueness in extensive social media datasets.

(a) Engagement Score (E): The Engagement Score assesses user interactions with content across digital platforms, incorporating various interaction types—including likes, shares, comments, and views—each assigned distinct weights based on their perceived value. To ensure comparability, the score is normalized on a scale from 0 to 1:

$$E = \frac{w_{\text{likes}} \cdot \text{Likes} + w_{\text{shares}} \cdot \text{Shares} + w_{\text{comments}} \cdot \text{Comments}}{MaxE} \tag{1}$$

In equation 1:

- w_{likes}, w_{shares}, and w_{comments} denote the weights for likes, shares, and comments, determined by their relative importance in indicating user engagement.
- $MaxE$ represents the maximum possible engagement score for normalization, ensuring consistency across various contexts. This formula provides a nuanced understanding of user engagement, enabling us to evaluate content resonance and identify interaction trends.

(b) Sentiment Score (S): The Sentiment Score quantifies the overall sentiment expressed in posts and comments, offering insights into user feelings regarding specific content. Normalized on a scale from 0 to 1, where 0 signifies entirely negative sentiment, 0.5 denotes neutral sentiment, and 1 indicates entirely positive sentiment, the Sentiment Score S is mathematically defined as follows:

$$S = \frac{N_{\text{positive}} - N_{\text{negative}}}{N_{\text{total}}} \tag{2}$$

Where:

- N_{positive} represents the count of positive sentiment indicators (e.g., positive comments).
- N_{negative} signifies the count of negative sentiment indicators (e.g., negative comments).
- $N_{\text{total}} = N_{\text{positive}} + N_{\text{negative}} + N_{\text{neutral}}$ is the total count of all sentiment indicators.

To normalize the Sentiment Score to the range $[0, 1]$, we apply the transformation:

$$S_{\text{normalized}} = \frac{S + 1}{2} \tag{3}$$

This normalization converts S from the range $[-1, 1]$ to $[0, 1]$, ensuring that negative sentiment scores yield values closer to 0, neutral scores yield 0.5, and positive scores yield values closer to 1.

(c) Category Readability Score (ρ): The Readability Score is critical for user persona development, as it assesses engagement based on the clarity and complexity of the language used in posts. This metric categorizes posts as follows:

- A score of 1 is given to posts written in simple language, making them accessible to a broad audience.
- Posts utilizing professional terminology receive a score of 2, targeting a demographic that values technical accuracy.
- Posts deemed unreadable due to poor grammar or excessive complexity are assigned a score of 0.

The aggregate Readability Score R for each user is computed by averaging the scores of all posts they have interacted with:

$$R = \frac{1}{N} \sum_{i=1}^{N} S_i \tag{4}$$

Here, R represents the user's aggregate Readability Score, based on N posts interacted with, where each post's individual score is denoted as S_i. This methodology provides a quantifiable measure of the readability of content that users engage with, facilitating a nuanced analysis of user preferences and interaction patterns—crucial for tailoring content strategies and enhancing user engagement.

(d) User Persona Score (C): The User Persona Score C_k quantifies a user's overall engagement and interaction quality within a specific content category k. It is calculated as a weighted sum of the Engagement Score E, Readability Score R, and Sentiment Score S, based on their relative significance. The formula for C_k is defined as follows:

$$C_k = w_E \times E + w_R \times R + w_S \times S \tag{5}$$

In this equation:

- C_k is the Persona Score for category k.
- E, R, and S are the respective scores.
- w_E, w_R, and w_S are the weights for these scores, satisfying the condition:

$$w_E + w_R + w_S = 1 \tag{6}$$

The Persona Score C_k initializes at zero and is computed by summing the weighted contributions of each component. This structured approach ensures a comprehensive assessment of user engagement, informing tailored content strategies for specific audience segments. The primary objective for the focus user is to gauge their interests in selected topics. For instance, as illustrated in figure 1, we analyze the proportion of interests expressed by the user, which is critical for delivering intelligent suggestions in our content filtering process.

Social Circle Analysis An in-depth understanding of the social circle of the focal user is essential for analyzing the dynamics between the user and their friends. This analysis allows us to differentiate between frequent friends—those characterized by regular interactions—and infrequent friends with less engagement. By examining these dynamics, we gain insights into the engagement factors that define the user's social interactions. Utilizing Selenium scripts and web crawlers, we extract posts associated with the user's social circle, compiling a dataset that reflects their interactions. The extracted content is categorized into text-based and video-based posts. For text posts, we employ a pre-trained Social GPT model (refer to figure 1) developed through our federated learning strategy to classify the content categories. For video posts, each video is converted into frames, transformed into base64 format, and analyzed using the same Social GPT model to determine their categories.
To enhance user experience further, we compute a 'user rank' for each individual in the user's social circle, derived from a scoring system that quantifies engagement with each friend's content. The engagement score for each friend is calculated as follows:

$$\delta_i = w_l \times L_i + w_c \times C_i + w_{sh} \times Sh_i \tag{7}$$

In this equation:

- δ_i represents the engagement score for friend i.
- L_i, C_i, and Sh_i denote the counts of likes, comments, and shares made by the user on friend i's content.
- The weights w_l, w_c, and w_{sh} reflect the importance of likes, comments, and shares in measuring engagement.

3.3 Smart Video Analysis

The second module of our system architecture focuses on storing metadata of videos to facilitate recommendations, follow-up videos, and smart querying based on user activity.

Smart Video Suggestions We analyze videos shared within the user's social circle by converting them into multiple image frames for content understanding. These frames are encoded in base64 format and processed through a pre-trained Social GPT model. Two key activities in this process include identifying the video category and extracting image descriptions for future querying.
(a) Video Category Analysis: We categorize videos and combine this information with user persona scores, storing the results in a database. This enables smart video suggestions based on these scores, as discussed in the user profiling section. For insights into the process of extracting video-to-text analysis.
(b) Knowledge Graph: This step is crucial for querying video content. We extract descriptions from videos using transcripts, convert them into embeddings, and store both descriptions and embeddings in a Neo4j database. We subsequently perform cosine similarity matching for user questions using the formula:

$$\text{cosine\_similarity}(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$

where $\mathbf{a} \cdot \mathbf{b}$ is the dot product, and $\|\mathbf{a}\|$ and $\|\mathbf{b}\|$ are the magnitudes of the embeddings.

Smart Video Query In the Smart Video Query component, users can search within selected videos, enhancing the interaction by allowing them to pose questions about the content. When a question is submitted, we identify the appropriate node in the Neo4j knowledge graph. The user's question is converted into an embedding, capturing its semantic meaning for effective retrieval. With the question embedded, we search the Neo4j database for the closest matching node based on cosine similarity to the embeddings of stored video descriptions. This process ensures the retrieval of relevant metadata and descriptions for the current video.
Utilizing a Retrieval-Augmented Generator (RAG), we enhance our response capabilities by integrating retrieval methods with generative techniques. We formulate a prompt using a role-based strategy and pass the user's question embedding along with extracted image information to the pre-trained Social GPT model. This model generates coherent and contextually relevant responses, enriching user interaction by providing precise answers tailored to the content being viewed.

3.4 Content Filtering

The final component of our system focuses on filtering content based on user preferences. We customize the content delivery system by filtering posts according to categories aligned with the user's persona score. For instance, if the score indicates a strong interest in sports, the system prioritizes sports-related content shared by highly engaged friends. This targeted approach enhances user engagement and content relevance.
The importance of each friend's post, denoted as P_i, is represented as follows:

$$P_i = w_C \cdot C + w_L \cdot L + w_S \cdot S + w_T \cdot \frac{1}{T}$$

where w_C, w_L, w_S, and w_T are the weights for comments, likes, shares, and recency. The variables C, L, and S represent the counts of comments, likes, and shares, while T denotes the time since publication, with $\frac{1}{T}$ rewarding more recent posts. Our refined filtering mechanism enables users to exclude posts with negative sentiment scores based on predictive trends in comments. Content is curated to align with individual preferences, categorizing non-targeted posts as general.
The filtering status F_i for each post i is determined as follows:

$$F_i = \begin{cases} 1 & \text{if } S_i > 0 \text{ and } T_i > \tau \\ 0 & \text{otherwise} \end{cases}$$

Here, τ is the threshold for trend prediction, and $F_i = 1$ indicates that the post passes the filter.

Readability Score (R) The Readability Score evaluates the ease of content comprehension, derived from the Flesch-Kincaid readability test based on word and sentence length. It is normalized to a scale of $[0, 1]$:

$$R = 1 - \frac{\text{Flesch-Kincaid Grade Level}}{MaxR}$$

where $MaxR$ is the maximum grade level for normalization, ensuring that the score reflects the accessibility of the content.

Adaptive Feedback Loop To enhance adaptability, we incorporate a user feedback mechanism. For example, if a user expresses interest in Community Services, tailored suggestions for that category are provided based on historical data. Recognizing evolving preferences, users can indicate likes or dislikes, which updates our database and refines future filtering criteria for more relevant suggestions. This feedback loop is also leveraged to build our evaluation datasets, improving response quality.

4 Experiments

4.1 Data Collection

Our data collection process utilizes a combination of web crawlers, Selenium scripts, and Jsoup to parse various social networks, enabling us to gather a diverse range of user-generated content. This approach allows us to extract engagement metrics, including likes, shares, and comments, from platforms such as Facebook, Twitter, and Instagram. In addition to this proprietary data, we also leverage several publicly available datasets to enrich our training corpus and enhance the robustness of our models [5].

4.2 Experimental Framework

Our experimental framework comprises four integrated modules, beginning with the development of a personalized Context-based Social Media Large Language Model (LLM) using a federated learning approach that prioritizes user privacy. We connected with four client entities, each deploying a foundational GPT-2 model trained on locally collected data from various social media platforms via our web crawler. Clients fine-tune the model with their data and send the updated parameters to a central global server for aggregation, as illustrated in Figure 1. This iterative process keeps our GPT model continually updated with fresh data, enhancing its adaptability for effective content filtering.
To categorize user posts, we employ advanced prompt engineering techniques, including role-based and few-shot prompting. Post categorization allows us to calculate user persona scores based on engagement history; for instance, if a user shows a 30% preference for politics and a 70% preference for sports, these insights inform content filtering. Our methodology employs quantitative metrics to assess user engagement and emotional resonance, resulting in a versatile Content Score to gauge content quality.

4.3 User Category Persona

User persona scores are derived from engagement metrics across categories like politics, sports, movies, and science. We focus on three primary interaction types—comments, shares, and likes—each assigned a weighted score based on their importance. Additionally, sentiment analysis enables users to filter out posts based on positive or negative sentiment, enhancing tailored content suggestions.

4.4 Content Filtering

This module identifies and ranks relevant posts from the user's friends list, assigning relevance scores based on a comprehensive engagement quantification approach. Posts are categorized by the Context-based GPT model, and the highest interaction scores inform the selection of trending content. This process occurs in near real-time, ensuring ongoing relevance as new posts are added.
Users can filter suggestions based on sentiment and provide feedback through like and dislike buttons, which dynamically adjusts future recommendations. An additional layer of filtering mitigates spam by employing a readability score algorithm to assess content quality.

4.5 Video Querying Framework

Our system supports dynamic querying, allowing users to ask specific questions about videos. User queries are converted into embeddings matched against descriptions stored in a Neo4j knowledge graph, utilizing cosine similarity to ensure contextually relevant responses, enhancing engagement and interaction.

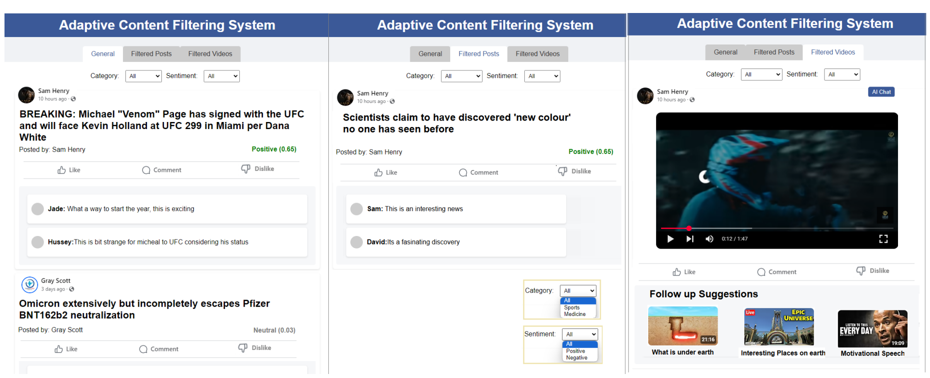

Fig. 2. The user interface of the proposed system for adaptive content filtering and smart video suggestions.

Table 1. Summarization statistics validated through various metrics.

Metrics	LoRA Federated	LoRA C1	LoRA C2	LoRA C3	LoRA C4
Rouge - 1	32.393	33.114	31.814	32.874	32.362
Rouge - 2	8.235	8.643	8.109	7.959	7.922
Rouge - l	26.794	25.929	25.398	25.394	26.809
BLEU - 4	8.324	8.922	8.325	8.457	8.342

Table 2. Performance Comparison on GLUE Benchmark

Model	RTE	MRPC	MNLI	QNLI	QQP	STS-B	SST-2
Centralized	58.4	76.4	75.2/76.5	86.6	86.5	81.7	89.1
FedAvg	52.6	72.2	70.9/71.7	83.6	84.6	73.3	86.0
Head-Emd Share	59.1	77.4	73.3/75.1	85.3	85.8	78.2	88.8
EmdAvg	51.2	73.7	69.9/70.8	81.4	84.0	70.7	83.8
Head-Emd Avg	56.9	71.2	70.8/72.5	84.0	85.1	74.5	85.7
Parallel FedAvg	58.7	71.5	71.1/72.7	82.7	84.6	75.3	84.9
Single Client	57.3	70.2	69.9/71.3	82.3	84.5	70.1	84.6

4.6 Performance Metrics

We evaluate various models, including LoRA Federated implementations and centralized approaches, across multiple NLP tasks, as shown in Tables 1, 2, and 3.

Key performance metrics include:

- *Rouge-1* [6]: Measures unigram overlap.
- *Rouge-2* [6]: Assesses bigram overlap.
- *Rouge-l* [6]: Evaluates the longest common subsequence.
- *BLEU-4* [8]: Compares n-grams in generated text to reference texts.

These metrics provide insights into model performance in summarization, language understanding, and text generation, facilitating informed decisions for further development.

Our experimental framework demonstrates the effectiveness of our federated learning approach, robust content filtering mechanisms, and adaptive querying capabilities. These promising results position our research as a significant contribution to privacy-preserving, contextualized machine learning applications in social media.

5 Evaluation

To thoroughly assess the value our system offers to its users, we conducted a user satisfaction survey involving 36 active participants of our platform. With 31 users responding, we achieved an 86 percent response rate. The insights derived from this survey highlight key factors influencing the overall user experience. The survey format was designed to precisely identify respondents through their usernames, linking their feedback to specific usage patterns. This identification was vital for a detailed analysis of elements affecting user satisfaction. The survey's second section aimed to gauge the relevance and appeal of the content suggested by

Table 3. Perplexity Comparison of Pre-trained GPT-2 Small

Model	Perplexity (PPL)
Centralized	25.25
FedAvg	23.25
Head-Emd Share	24.69
EmdAvg	39.03
Head-Emd Avg	39.52
Single Client	38.71

our platform. Users rated their interest in these recommendations and how well they aligned with their preferences. This feedback was crucial for assessing our content curation algorithm's effectiveness and pinpointing areas for improvement. Analyzing responses from the 31 participants, we gained valuable insights into our system's strengths and shortcomings, laying a groundwork for strategic enhancements. These findings, discussed in this conference paper, contribute to broader discussions on user satisfaction in digital environments, emphasizing the necessity of continual refinement of our services to meet and exceed user expectations.

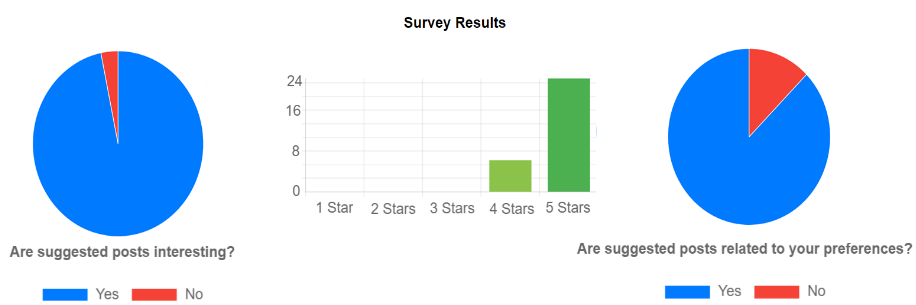

Fig. 3. The survey results feature three graphs: user content interest, overall system rating, and post relevance based on user preferences.

6 Conclusion

In conclusion, this study presents a novel contextualized federated learning framework that effectively addresses the critical challenges of user privacy and personalized content delivery in social media environments. By enabling users to collaboratively enhance a global large language model (LLM) without sharing sensitive data, our approach safeguards privacy while facilitating compliance with regulations. Through techniques such as Smart Video Querying and Adaptive Content Filtering, we deliver real-time, personalized recommendations that resonate with diverse user preferences. The mathematical formulation and convergence proof of our federated learning algorithm ensure robust model performance, while user profiling and persona analysis enhance engagement. Overall, our methodology establishes a pioneering solution that transforms social media interactions, prioritizing both data security and user-centric experiences in an increasingly digital landscape.

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