Indian Journal of Information Sources and Services
ISSN: 2231-6094 (P) Vol.15, No.3, 2025, pp.98-107

DOI: https://doi.org/10.51983/ijiss-2025.IJISS.15.3.11

Personalized Information Retrieval Systems: Enhancing User Interaction through Context-Aware Technologies

Sushmitha Prabhu[1*], Dhruv Kumar[2], Dr. Ramya G Franklin[3], Dr. Banalata Pradhan[4], Dr. Savita[5] and Dr. Duryodhan Jena[6]

[1*]Assistant Librarian, Learning Resource Centre, JAIN (Deemed to be University), Bangalore, Karnataka, India
[2]Research Scholar, Centre for Research Impact and Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India
[3]Associate Professor, Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, India
[4]Librarian, Department of Humanities and Social Sciences, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India
[5]Assistant Professor, Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh, India
[6]Professor, Department of Management, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, Odisha, India
E-mail: [1]sushmithaprabhu45.sp@gmail.com, [2]dhruvkumar.soni@chitkara.edu.in, [3]ramyagfranklin.cse@sathyabama.ac.in, [4]bnpiter@gmail.com, [5]savita@muit.in, [6]duryodhanjena@soa.ac.in
ORCID: [1]https://orcid.org/0009-0001-9459-2435, [2]https://orcid.org/0009-0007-7189-8179, [3]https://orcid.org/0000-0002-5139-5837, [4]https://orcid.org/0000-0003-3703-9788, [5]https://orcid.org/0000-0002-4826-4721, [6]https://orcid.org/0000-0002-9025-0905

(Received 19 May 2025; Revised 03 July 2025, Accepted 18 July 2025; Available online 30 September 2025)

Abstract - **The explosive growth of mobile Internet usage has led to an overwhelming proliferation of mobile applications. This phenomenon, commonly referred to as app overload, has resulted in significant challenges for users in identifying relevant and valuable content. Traditional recommendation systems often rely solely on historical usage data, neglecting critical contextual information, which led to suboptimal performance in dynamic usage environments. To address these challenges, this research introduces a Context-Aware Personalized Information Retrieval System (CAPIRS) that integrates a novel deep learning-based approach to enhance user interaction by capturing individual preferences across contextual scenarios. CAPIRS employs a dual-portrait modeling strategy, constructing comprehensive representations of both users and apps by incorporating attribute and contextual features. An Efficient Shark Search-driven Self-Attention-based Long Short-Term Memory (ESS-SLSTM) model is employed to accurately predict the probability of user engagement. Real-world data comprising user, app, and contextual interactions were collected from mobile platforms spanning diverse environments, temporal conditions, and demographic groups. Preprocessing involved data cleaning, deduplication and normalization of numerical features. Semantic features from textual app data were extracted using Term frequency-inverse document frequency (TF-IDF), while contextual attributes were embedded and structured into a tensor-based format for improved learning efficiency. Experimental results demonstrate that CAPIRS significantly outperforms traditional and benchmark methods in Precision@N, Recall, and Mean Average Precision (MAP) across personalized app recommendation tasks. This research underscores the importance of combining deep learning with context-aware technologies to develop more intelligent, adaptive, and user-centric information retrieval systems.**

Keywords: **Context-aware Computing, Information Retrieval Systems, Personalized Recommendation, User–App Interaction, Mobile Applications, Efficient Shark Search-Driven Self-Attention Based Long Short-Term Memory (ESS-SLSTM)**

I. INTRODUCTION

In an era where information overload is a prevalent fact, the capability to extract pertinent information tailored to individual needs is gaining prominence. Most traditional search engines and information retrieval (IR) systems are keyword-matching or ranking algorithm-based, without knowledge or consideration of the user's actual needs, intent, preferences, or contextual circumstances. Personalized Information Retrieval (PIR) systems attempt to circumvent this limitation by customizing the result list according to characteristic profiles, habits, and contextual situations of individual users, thereby enhancing the user experience (El-Ansari et al., 2021). Artificial intelligence (AI) has changed the way information processing and retrieval works (Ali, 2017). This revolutionary innovation leads the system to mimic human-like comprehension and decision-making powers. In PIR, AI was used to create learning models that adapt to users' preferences and patterns of behavior. This implies that, with AI, an IR system can move away from the purely rule-based control mechanism and instead migrate to systems that are more intelligent, and sensitive to the user's needs (Sansone & Sperlí 2022).

Machine Learning (ML) involves personalized information processing and retrieval models that are used for collaborative filtering, content-based filtering, or hybrid recommendation models (Rakesh, 2024). One can collect data on users' previous inferences and assume the preferences of the user under consideration (Mileva & Tikvesanski, 2022). Based on queries input by users into the system, it analyzes their clicked pages, time spent on them, and even the queries they put in (Yang & Singh, 2024). However, traditional models of ML are very dependent on structured datasets, where features need to be severely examined, for which they lack flexibility and cannot easily adapt to the changing needs of users (Meesad, 2021). With the advent of Deep Learning (DL), sophisticated and powerful models' such as neural networks, recurrent neural networks, and transformers have begun to find their way into information processing and retrieval systems (Boudjadar et al., 2025). The implication is that DL models learn high-level abstractions from unstructured data such as text and images; these high-level abstractions may work towards the understanding of semantic relationships and user intent. Nevertheless, DL in IR systems indeed requires large, sometimes extremely large datasets; they need heavy computational capabilities and yet lack explainability and the ability to take context into serious consideration when responding to queries, especially when real-time interaction is demanded (Dalimunthe & Hayadi 2022).

Even though information processing and retrieval have drastically changed under AI, ML, and DL, certain limitations indeed exist. Very few systems provide powerful context awareness, most of the time ignoring temporal, spatial, or situational aspects affecting the user's behavior in retrieval. Privacy issues, data sparsity, cold-start problems, and interpretability of personalized results remain a challenge for efficacy and even trust in PIR systems (Gunalan et al., 2023). These limitations indicate the need for more holistic, adaptable, and user-aligned solutions (Izacard et al., 2021). Despite the major advances in IR systems, they are limited in many ways, which makes these systems ineffective in personalized and context-sensitive applications. One key limitation is in using context, where systems do consider changing user factors such as time, location, device, and activity. As a result, the systems generate very generic and less relevant results. Another issue that has existed forever is that information processing and retrieval lack the cold-start problem, which occurs when new customers or new content appear with less data to be accurately personalized. Associated with the sparsity of data, limited interaction data undermines the system's ability to form any meaningful learning of user preference (Braun, 2021).

Many information processing and retrieval systems face challenges regarding explainability, particularly those based on complex ML or DL, thus complicating materials for users who could not easily trace back why certain results were recommended. In addition, the issues related to scalability of systems must also efficiently deal with huge amounts of data and user interaction in real-world deployment scenarios. User intent remains somewhat ambiguous because systems misinterpret vague or multi-meaning queries due to an absence of contextual signals (Abu-Rasheed et al., 2022). The research mainly focuses on designing a Context-Aware Personalized Information Retrieval System (CAPIRS) so that users can significantly interact more with the application through the integration of DL and contextual modeling approaches wherein the user's true state is accurately predicted, thus leading to delivering very precise app recommendations in dynamic mobile environments.

II. RELATED WORKS

The integration of DL and symbolic reasoning can enhance knowledge retrieval in Large Language Models (LLMs) (Xiong & Zheng, 2024). The on-device AI application, combined pattern recognition with rule-based logic, evaluated the information processing and retrieval tasks. The result showed improved accuracy, logical coherence, and rule adherence as compared to baseline models. It may run into challenges of scalability with more complex symbolic reasoning and generalization concerning an array of diverse real-world contexts. When machine learning (ML) and deep learning (DL) techniques were applied to user data, the effects of increased screen time on mental health cuold be examined (Pandey & Sharma, 2023). The analytical study compared two types of conversational AI systems: generative chatbots retrieval-based chatbots. The analysis indicated that the accuracy of the generative chatbots was higher at 94.45%, compared to the retrieval-based chatbots (83.22%). The research was confined to the interaction with chatbots and does not consider any further psychological or environmental variables.

The refine information processing and retrieval through prompted paraphrasing version 2 (InPars-v2) was done, a system that generates synthetic query-document pairs via open-source LLMs and rankers (Jeronymo et al., 2023). The technique was a substitution for proprietary models, which were the backbone of earlier systems like Propagator and InPars. It achieved state-of-the-art results on the benchmarking IR (BEIR), promoting reproducibility by releasing data and models. However, the dependence on the extant rankers limited the diversity that was achieved in the generated queries. The research created a CAPIR system that strived to increase the relevance of search results by incorporating an evolutionary ML approach with context-related parameters such as user behavior, location, and time (Lopez et al., 2025). The methodology used continuous learning to adapt user interaction and feedback. Results obtained from empirical and quantitative methods showed an increase in the contextuality of response for information processing and retrieval systems. Nevertheless, limitations were posed in terms of computational complexity and scalability issues when implementing real-time scenarios with large-scale deployment. An information search model and an open-ended conversational agent were developed that used a finite state machine for intranet document retrieval and corporate document retrieval (Rateria & Singh, 2024). It relied on contextual search using bidirectional encoder representation from transformers (BERT) based word representations without requiring extensive training data. Experimental results indicated improved relevance over BERT with cosine similarity and best matching (BM25). Limitations included restricted domain adaptability and reduction of flexibility on complex, multi-turn conversational queries (Rateria & Singh, 2024).

To enhance the usability of electronic design automation (EDA) tools, a ML-based information processing and retrieval systems were introduced that interpreted user queries using natural language processing (NLP), retrieved appropriate information, and eventually delivered context-sensitive assistance (Kumar & Mehr, 2024). The information processing and retrieval system facilitated the interaction of users with computer-aided design tools and EDA tools, which can be quite complex. This benefit dropped down to users across different levels of expertise. However, the system yet had its limitations, namely, dependence on the performance of domain-specific language models and difficulty handling very technical or ambiguous queries.

An end-to-end data-retrieval framework called Self-Retrieval was implemented by a large language model (Tang et al., 2024). Self-supervised learning was applied to internalize the corpus, hence turning the information processing and retrieval into sequential passage generation and relevance assessment for reranking. Experimental results showed improved performance in downstream applications for LLM as compared to existing techniques. The research lacked scalability with increased corpus size, and dependency on quality training data was also mentioned. The NLP was used for retrieval employing hybrid BERT model (Shaik et al., 2024). The methods applied were fine-tuning on input BERT and extracting paragraphs; optimization was done using the Adaptive Improved Arithmetic Optimization (AIAO) approach. The model performed well with Precision (0.700), Recall (0.767), F1-Score (0.732), Bleu Score (0.721), and RIBES (0.776). The suggested model includes possible problems with scalability and domain adaptations.

III. METHODOLOGY

Initially, the proposed method involves the collection of data from different mobile environments and the preprocessing is done by using cleaning, de-duplication, and normalization. The identification of semantic features from the extracted terms is performed by considering the weighting scheme of Term frequency-inverse document frequency (TF-IDF), whereas tensor embedding is used for contextual attributes. Incorporating contextual and attribute features, the proposed ESS-SLSTM model is capable of capturing accurate predictions of user engagement to enhance recommendations personalized to the user with a dual-portrait user-app representation. Fig. 1 shows the ESS-SLSTM workflow involved in CAPIRS.

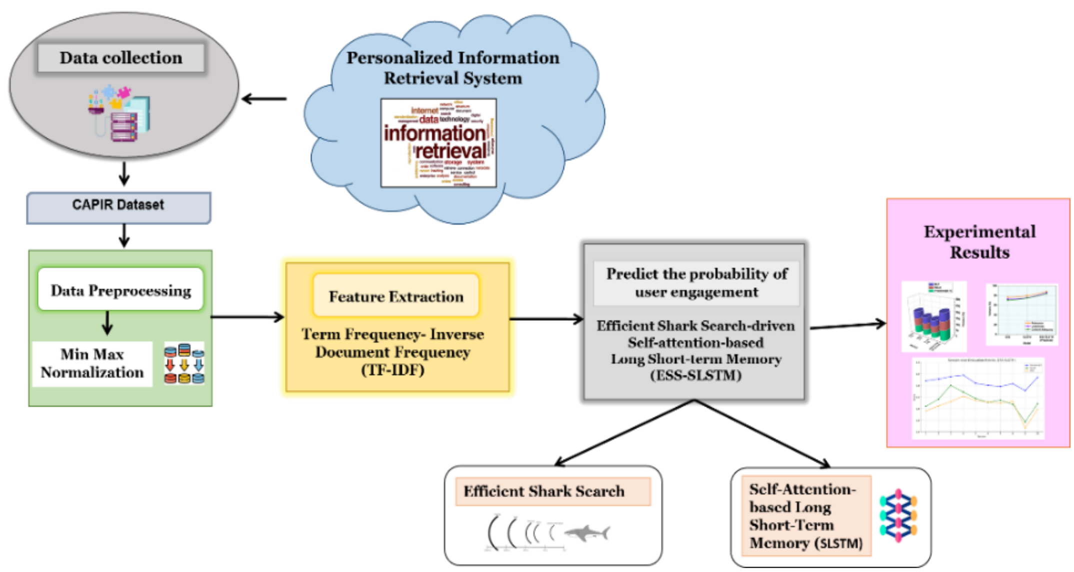

Fig. 1 Methodology framework for Proposed Context-Aware Personalized Information Retrieval System (CAPIRS)

Context-Aware Personalized Information Retrieval System (CAPIR)

By integrating DL with contextual modeling for personalized results, CAPIRS enhances user interaction. It utilizes a state-of-the-art dual-portrait modeling strategy, which leads to rich representations of the user and application incorporating semantic, attribute, and contextual features. In a nutshell, the ESS-SLSTM model predicts user engagement as an output based on the input data while capturing real-world dynamic patterns from the contextualized interaction itself. CAPIRS acts on raw data with massive feature generation and, thus, provides on-time real recommendation results for these dynamic systems, creating comparative advantages over traditional technologies in personalization and relevance scores.

Data Preparation

The CAPIR data was collected from open-source Kaggle: https://www.kaggle.com/datasets/programmer3/capirs-user-app-interaction-dataset.This dataset is intended for use in CAPIRS research and development. In addition to contextual information like geolocation at the time of usage, network type, battery life, weather, and time of day, each record in the collection symbolizes an interaction between a user and an app. additionally, it comprises significant goal factors.

The preprocessing involves data cleaning that employs handling missing values, correcting inconsistencies, and standardizing numerical formats. Duplication records were eliminated through data de-duplication.

- **Data cleaning:** This process consists of the removal of irrelevant, incomplete, or incorrect data. This may involve handling missing values, fixing formatting errors, and sorting out and purging noisy or corrupted entries so as to ensure consistency and accuracy in the data set for an improved model training quality.

- **Deduplication:** It consists of identifying and removing repeated records in the dataset, such as duplicate user interactions or app entries. It prevents redundancy, avoids biased learning, and ensures that the model gets trained with unique and meaningful data points for accurate predictions.

Min-Max Normalization of Numerical Methods

After data cleaning and duplication, Min-Max normalization was applied to numerical features. This procedure scales each feature to a predetermined range of 0 to 1. It brings all of the features into a common region so that they can fit in with the varying data magnitudes and hence, accelerate model training during the actual learning phase. Equation (1) shows the normalization process.

$$\mathrm{W_{new}} = \frac{\mathrm{W-min(w)}}{\mathrm{max}(w)-\mathrm{min(w)}} \tag{1}$$

- $\mathrm{W_{new}}$-The adjusted value derived from the normalized outcomes

- W- Previous value

- max(w)-The dataset's maximum value

- min(w)-The dataset's minimum value

Feature extraction using the Term frequency-inverse document frequency (TF-IDF)

Feature extraction is the process of converting raw data into useful information for ML models. In this research, TF-IDF is utilized to extract semantic features from app descriptions, emphasizing contextually relevant terms to improve personalization; it was shown in equation (2).

$$TF_{s,c} = \frac{e_{s,c}}{\max\{e_{s',c'},s,\in c\}} \tag{2}$$

The term $TF_{s,c}$refers to the count of the frequencies of terms in a document, which is a sign of their importance in the document.$e_{s,c}$is the number of occurrences of the term s in the context c.

$$IDF_{s,c} = log\frac{C}{(c\in C.s+\in c\}} \tag{3}$$

$IDF_{s,c}$Measures how rare a term s is in across all contexts$c$, thus reducing the weight of many common terms and improving the distinctive and informative measures for improved feature representation in information processing and retrieval. Equation (4) represents TF-IDF-based semantic weight used in personalized retrieval.

$$TF - IDF = TF_{s,c} \times IDF_{s,c} \tag{4}$$

The TF improves personalized feature extraction in the modeling of user-app interaction by assigning each term contextual importance, combining its normalized frequency in a specific app context and its uniqueness across all the contexts.

Efficient Shark Search-driven Self-Attention-based Long Short-Term Memory (ESS-SLSTM)

The ESS-SLSTM model adds the global optimization capability of the ESS algorithm to the contextual sequence modeling strength of SLSTM that can result in robust personalization through adaptive learning of user-app interaction patterns in dynamic, complex environments.

Long Short-Term Memory (LSTM)

LSTM is a recurrent neural network designed to model sequential data by capturing long-range dependencies and temporal patterns. It uses memory cells and gating mechanisms to keep relevant information for long periods, which perfectly fits the requirements for personalized information retrieval concerning user behaviors and contextual sequences.

$$j_s = \sigma(X_j.[g_{s-1}, w_s] + a_j) \tag{5}$$

The concatenation of previous state and current input w_s is passed through the sigmoid activation to compute the update gateg_{s-1}, making possible context-aware learning adaptively. Equation (6) updates gate computation enabling dynamic integration of sequential context input features for information processing and retrieval system.

$$e_s = \sigma(X_e.[g_{s-1}, w_s] + a_e) \tag{6}$$

Model $e_s$computes the contextual embedding of a term s, where past state g_{s-1} and current word $a_e$vector is combined and activated to capture information processing and retrieval semantic features. Equations (7-10) denote gated feature fusion process in user-application interaction modeling.

$$\overline{D}_s = \tanh\,(X_{\overline{D}}.[g_{s-1}, w_s] + a_{\bar{d}} \tag{7}$$

$$D_s = e_s \,.\, g_{s-1} + j_s . D_{\bar{s}} \tag{8}$$

$$p_s = \sigma(X_p.[g_{s-1}, w_s] + a_p) \tag{9}$$

$$g_s = p_s . tanhD_s \tag{10}$$

The above equations represent the gated feature fusion mechanism in the retrieval system. The $\overline{D}_s$ uses past state and word context. The above equation refines it with contextual weights. Compute the control gate p_s and the updated hidden state g_s to enhance personalized context-aware learning. Fig. 2 shows the LSTM networks employed to model sequential user-app interactions by capturing temporal patterns and contextual dependencies. This enhances the capability of the system to provide timely information retrieval results that are personalized.

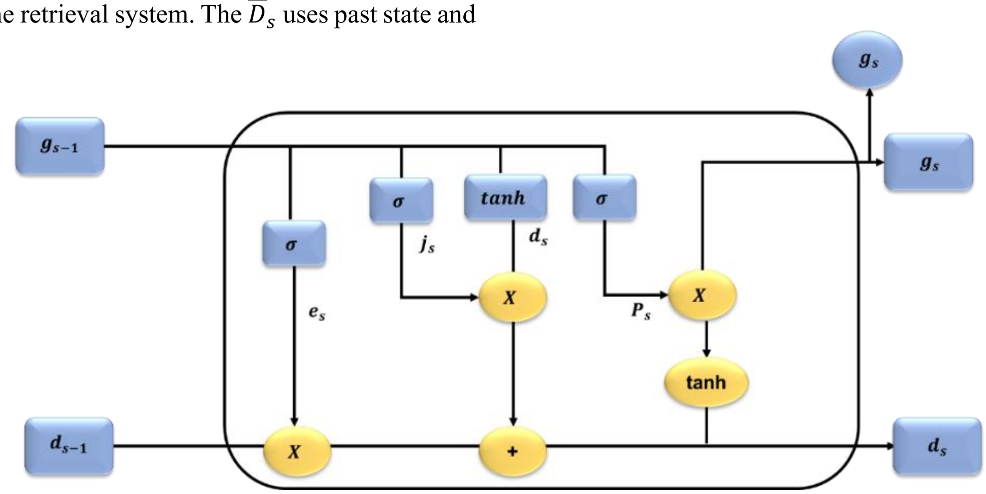

Fig. 2 LSTM Architecture

Global – Local Self Attention

This model creates a complete context with a prominent yet angulated focus that captures worldwide patterns across the sequence and the localized dependencies in their smaller sections. Dual attentiveness, which is also present in information processing and retrieval systems, improves the model's ability to decipher user behavior and contextual cues to provide more precise recommendations. Equations (11-13) show the self-attention mechanism in ESS-SLSTM for capturing hierarchical contextual dependencies in personalized information retrieval. Fig. 3 shows the selfattention-based LSTM.

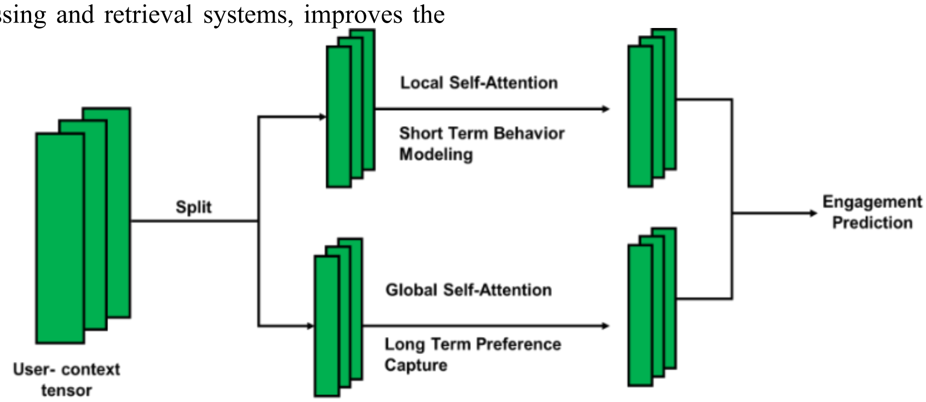

Fig. 3 Architecture of the ESS-SLSTM Model in IR system

$$W = [W_1, W_2, \ldots, W_M], M = \frac{S}{x} \tag{11}$$

$$head_l = \begin{cases} LocalAttentio_l(W), l = 1, \ldots, \frac{l}{2} \\ LocalAttention_l(W), l = \frac{l}{2} + 1, \ldots, L \end{cases} \tag{12}$$

$$GL - Attention(W) = cat(head_1, \ldots, head_l)X \tag{13}$$

The input sequence$[W_1, W_2, \ldots, W_M]$ is divided into $\frac{S}{x}$ segments for localized attention process. The local attention $LocalAttentio_l(W)$ is applied across halves of the layers to capture fine-grained contextual relevance. The global local self attention output aggregates all attention heads to enhance user app interaction modeling. Thus, SLSTM combines the sequential learning strength of LSTM with the contextual focus of self-attention, enabling the model to capture both temporal dependencies and global contextual relevance, thereby enhancing personalized user-app recommendations in dynamic environments.

Efficient Shark Search (ESS)

Once the personalized information retrieval optimization begins, the ESS algorithm randomly initializes a diverse population of hypothetical solutions. In a d-dimensional feature space, each vector signifies an interaction pattern between the user and the app candidate. In this structure modeled as 2D, Equation (14) shows that the contextually evolving population size m is used.

$$O = \begin{bmatrix} O_1^1 \; O_2^1 \dots O_c^1 \\ O_1^2 \; O_2^2 \dots O_c^2 \\ \vdots \quad \vdots \; \cdots \; \vdots \\ O_1^m O_2^m \cdots O_c^m \end{bmatrix} \quad (14)$$

This refers to the locater m^{th} across all the candidate solutions in the O^{th} feature dimension under the ESS-SLSTM model. Ithas the detachment of upper O_c^m and lower O_c^1 bounds of the semantic-contextual search space. To optimally guide personalization, equation (15) is formulated.

$$O_i^j = ka_i + rand \times (va_i - ka_i) \quad (15)$$

The O_i^j generates the initial solution in the schematic contextual space, where ka_i and va_i are the lower and upper bounds. This helps to explore diverse user application interaction patterns during optimization, for information processing and retrieval system.

$$u_{l+1}^j(\mu(u_l^j + s_1[O_{hbest_l} - O_l^j] \times d_1 + s_2[O_{best}^{u_l^j} - O_l^j] \times d_2) \quad (16)$$

The above equation updates the position u_l^j of a candidate solution by combining its current state u_l^j with guided movement toward the historical best O_{hbest_l} and global best $O_{best}^{u_l^j}$ enhancing personalized feature optimization through adaptive exploration. Equation (17) represents random contextual factor for enhancing exploration ESS-based optimization model.

$$\mu = [m \times rand(1, m)] + 1 \quad (17)$$

A randomly selected influence factor from m context features is $rand(1, m)$, which introduces variability into the optimization process, thereby better adapting personalized user-app matching.

$$\begin{cases} s_1 = s_{max} + (s_{max} - s_{min}) \times f^{-\left(\frac{4l}{L}\right)^2} \\ s_2 = s_{min} + (s_{max} - s_{min}) \times f^{-\left(\frac{4l}{L}\right)^2} \end{cases} \quad (18)$$

$$O_{l+1}^j = \begin{cases} O_l^j \times \neg \oplus O_p + vb + k \times a; rand < nu \\ O_l^j + \frac{u_l^j}{e}; \; rand \geq nu \end{cases} \quad (19)$$

$$b = sgn\left(O_l^j - v\right) > 0 \quad (20)$$

$$a = sgn\left(O_l^j - k\right) < 0 \quad (21)$$

$$O_{l+1}^j = O_{gbest_l} + q_1 \vec{C}_\omega \times sgn(q_2 - 0.5), q_3 < T_t \quad (22)$$

$$\vec{C}_\omega = |rand \times \left(O_{gbest_l} - O_l^j\right)|$$

The above equations demonstrate the adaptation of the optimization dynamics modeled in ESS-SLSTM. The parameters balances the exploration and the exploitation using O_{l+1}^j random thresholds, local and global bests, and sign-based movement, eventually guiding the model toward optimal personalized retrieval.

$$T_t = |1 - f^{-\left(-b2 \times \frac{l}{L}\right)}| \quad (23)$$

The term T_t dynamically adjusts the threshold over iteration. It controls the balance between optimization of user application contextual relevance. Equation (24) enhances the personalized feature convergence in user app interaction modeling.

$$O_{l+1}^j = \frac{O_l^j + O_{l+1}^j}{2 \times rand} \quad (24)$$

The equation O_{l+1}^j refines the solution by averaging the current and updated positions, scaled by randomness to introduce diversity. This enhances the personalized feature convergence in user-app interaction in information retrieval systems. The ESS fine-tuned the model SLSTM, and refined personalized app recommendations through the architecture by aligning contextual embeddings with user preferences. This allows the performance of dynamic environments to static classifiers in terms of accuracy and relevance. Algorithm 1 shows the ESS-SLSTM model, an information retrieval system.

Algorithm1: Efficient Shark Search-driven Self-Attention-based Long Short-Term Memory (ESS-SLSTM)

Initialize SLSTM model parameters

→ Initialize weights, memory cells, and gates (input, forget, output)

→ Apply self-attention across temporal inputs for each session

Initialize ESS Optimization Parameters

→ Set population size n

→ Define search space bounds: ka_i (lower),va_i (upper)

→ Generate initial population O using:

$$O_i^j = ka_i + rand \times (va_i - ka_i)$$

for each iteration l = 1 to Max_Iter do

for each solution O_{l+1}^{j} in the population do

Compute SLSTM contextual embedding:

$$e_s = \sigma(X_e.[g_{s-1}, w_s] + a_e)$$

Update gates:

$$j_s = \sigma\left(X_j.[g_{s-1}, w_s] + a_j\right)$$

Fuse gated outputs:

$$\overline{D}_s = \tanh\,(X_{\overline{D}}.[g_{s-1}, w_s] + a_{\overline{d}}$$

$$D_s = e_s\,.\,g_{s-1} + j_s.D_{\bar{s}}$$

$$g_s = p_s._{\ this}$$

Apply Global-Local Self-Attention:

Divide input W into M segments

Compute local attention heads

Concatenate global context: GL-Attention(W)

Evaluate fitness using retrieval metrics (P@5, MAP, Recall)

Update population using ESS rules:

s_1, s_2 ← adaptive weights

μ ← random contextual influence

if $rand < v$ then

$$O_i^j = ka_i + rand \times (va_i - ka_i)$$

else

$$O_{l+1}^j = O_{gbest_l} + q_1\vec{C}_\omega \times sgn(q_2 - 0.5), q_3 < T_t$$

Compute thresholds and sign movement:

$$T_t = |1 - f^{-\left(-b2\times\frac{l}{L}\right)}$$

if $q_3 < T_t$ then

$$\vec{C}_\omega = |rand \times \left(O_{gbest_l} - O_l^j\right)|$$

end if

Refine position:

$$O_{l+1}^j = \frac{O_l^j + O_{l+1}^j}{2 \times rand}$$

end for

Update global best O_{hbest}

end for

Return: Personalized Retrieval Ranking from best g_s

IV. RESULT AND DISCUSSION

This section demonstrates the experimental outcomes of the proposed model, showcasing detailed performance evaluation results. It involves further comparative analysis against existing methodologies in order to improve aspects of the proposed method. Utilization of Python 3.11.4 for implementation of algorithms, experimentation was performed on a high-performance machine having 64 GB of RAM and an AMD Ryzen 5900X processor running Windows 11. This made for very efficient training and evaluation processes for the proposed ESS-SLSTM model.

Performance Analysis

The evaluation metrics for ESS-SLSTM included precision at 5 (P@5), recall, and Mean Average Precision (MAP) during a series of experimental sessions. As per Table I, and Fig.4, the results corroborate ESS-SLSTM's potential to provide accurate context-aware recommendations, outperforming traditional IR and baseline models by a significant margin.

Precision: It is the ratio of relevant items retrieved from the total number of items recommended to the user by the system. The precision of the model indicates how accurate and relevant the results delivered by this model are.

Recall: The term recall expresses the capacity of a model to retrieve all relevant items within a total set of pertinent data. It determines how well the system retrieves useful content for the user.

MAP: The metric MAP is an interface evaluation technique that calculates the average precision over a number of queries and thus signifies both the correctness and ranking quality of the retrieved results in personalized recommendation environments.

TABLE I PERFORMANCE METRICS OF ESS-SLSTM ACROSS EXPERIMENTAL SESSIONS

Session	Precision@5 (P@5)	Recall (R)	MAP
1	0.842	0.621	0.582
2	0.856	0.683	0.624
3	0.878	0.802	0.662
4	0.891	0.744	0.709
5	0.820	0.689	0.672
6	0.803	0.655	0.658
7	0.792	0.674	0.649
8	0.817	0.638	0.665
9	0.756	0.487	0.432
10	0.872	0.643	0.597

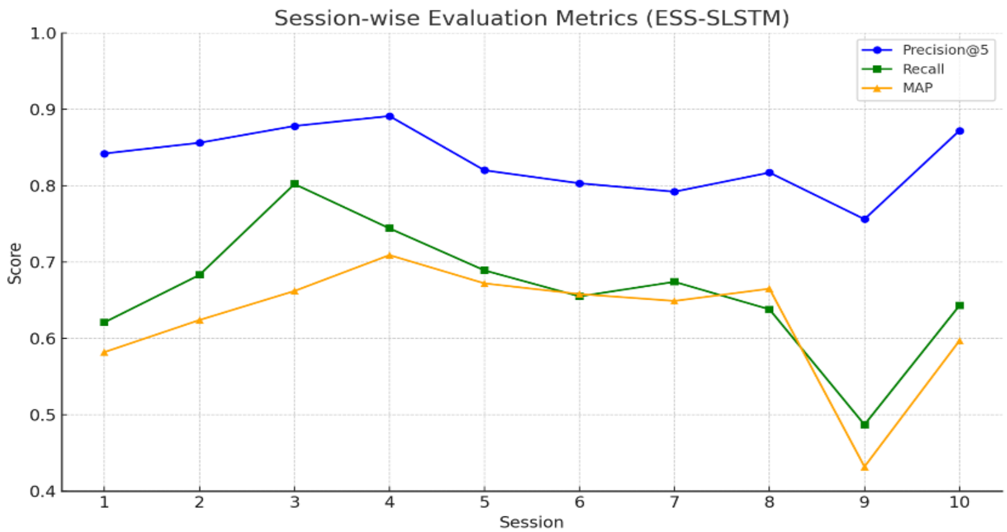

Fig. 4 Precision, recall, and MAP score for ESS-SLSTM

Table I shows the performance of the proposed ESS-SLSTM model for 10 experimental sessions on the three important metrics of Precision@5 (P@5), Recall (R), and MAP. Precision@5 values were consistently high, with a peak of 0.891, which shows a strong tendency of the model to recommend top-relevant results. On the contrary, recall shows good coverage of relevant items, and MAP indicates precision in the overall ranking. If the scores were high and stable among the experimental sessions, it is interpreted that the proposed model is robust and adaptable in providing personalized context-aware information retrieval.

Comparison Phase

In the comparison phase, CAPIR (Singh & Boursier,2024), BM25 (Singh & Boursier,2024), and TF-IDF (Singh & Boursier,2024) models were measured against the proposed ESS-SLSTM model. Experimental results show that the proposed model substantially outperforms existing models on Precision@5, Recall, and MAP, indicating the method's strong ability to model the interaction between users and apps in a context- and personalized manner, particularly by considering factors such as behavior, time and contextual relevance. Table II and Fig. 5 show the Precision@5, Recall, and MAP values for CAPIR, BM25, TF-IDF, and offered ESS-SLSTM model, which are all said to have performed better than the rest in all evaluation metrics, substantiating the proposed model's efficacy for personalized information retrieval tasks.

TABLE II COMPARISON ANALYSIS OF PERFORMANCE METRICS

Method	Precision@5 (%)	Recall (%)	MAP (%)
CAPIR (Singh & Boursier,2024)	63.0	62.4	58.7
BM25 (Singh & Boursier,2024)	47.3	54.1	50.2
TF-IDF (Singh & Boursier,2024)	44.8	52.7	48.5
ESS-SLSTM [Proposed]	85.6	72.3	66.5

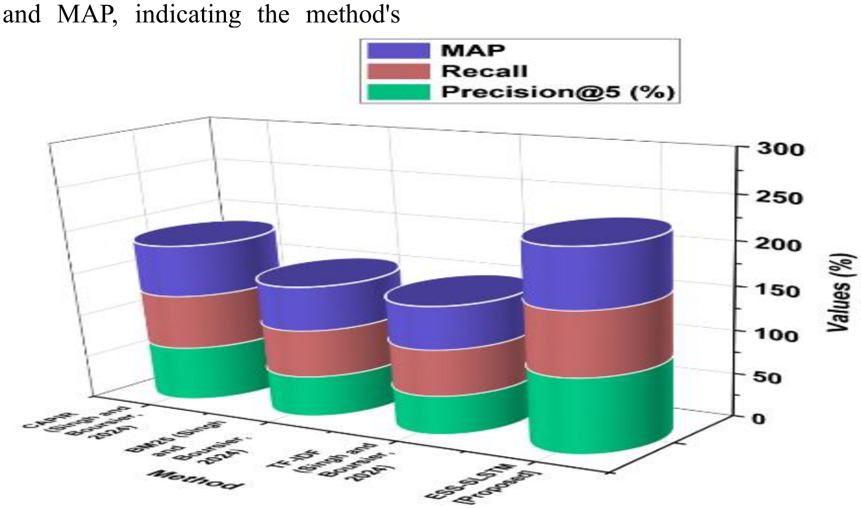

Fig. 5 Performance Comparison of ESS-SLSTM Model

The above information retrieval methods, such as CAPIR, BM25, TF-IDF, and ESS-SLSTM, were evaluated based on precision@5, recall, and MAP metrics. The performance of all these methods is low compared to the proposed method of

ESS-SLSTM. Further, the proposed model achieves 85.6% precision, 72.3% recall, and 66.5% MAP. Therefore, the superiority of the model in capturing personalized and contextual user preferences compared to traditional methods, which are context-unaware and lack deep learning integration, is validated for the proposed approach in dynamic recommendation environments.

Evaluation of Model Components

Performance evaluation of model components establishes the efficacy of each module, i.e. context embedding, self-attention, and the ESS optimizer, through comparison of both independent and joint performance impacts. This baseline assessment demonstrates that each component contributes meaningfully to overall retrieval accuracy. Table III and Fig.6 show the evaluation of relevance, usefulness, and content adequacy in personalized information retrieval tasks.

TABLE III PERFORMANCE EVALUATION BASED ON CONTEXT-AWARE PERSONALIZED IR SYSTEM

Model	Relevance (%)	Usefulness (%)	Content-Adequacy (%)
ESS	76.2	72.4	70.1
SLSTM	79.6	75.3	74.8
ESS-SLSTM [Proposed]	88.3	85.6	83.9

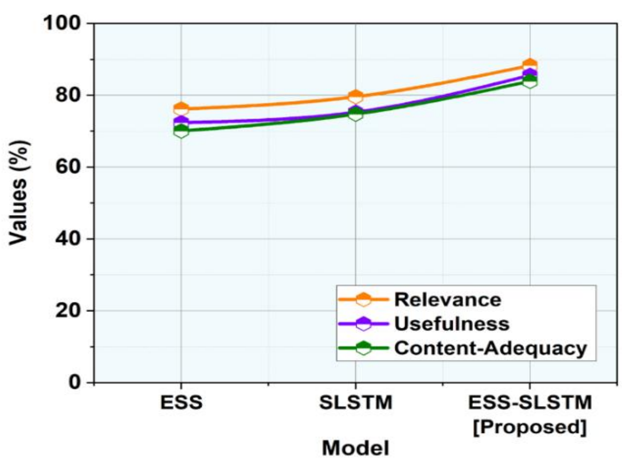

Fig. 6 Outcome of Evaluation Model Components

The relevance, usefulness, and content-adequacy of the three models: ESS, SLSTM, and the proposed ESS-SLSTM, are compared in Table III. With 88.3% relevance, 85.6% usefulness, and 83.9% content-adequacy, the ESS-SLSTM appears to have the upper hand over the others, as it has a greater ability to understand user preferences and contextual behavior. These results validate the model's effectiveness in providing highly personalized and context-aware recommendations for mobile information retrieval systems.

V. Discussion

The CAPIR is a method used for contextual personalized information retrieval based on dynamic user behavior; BM25 is effective for keyword relevance but does not consider the semantic similarity and temporal patterns or even TF-IDF. For instance, a simple basic weighting system that doesn't factor context dependency-user intent-interaction history into the equation is a major challenge. Such limitation narrows down its application for personalized retrieval. The proposed ESS-SLSTM method is a combination of SLSTM and ESS, capable of capturing sequential dependencies as well as contextual semantics. It improves personalized information retrieval by dynamically modeling user behavior, contextual relevance, and interaction patterns. This hybrid approach, therefore, enhances recommendation accuracy, adaptability, and precision; hence, it is better than traditional IR techniques when applied to dynamic and complex user-app situations.

VI. Conclusion

CAPIRS was addressed by the constant dilemma of application overload as a result of heavy mobile usage. The research aimed at improving personalized recommendations of apps through the incorporation of contextual and behavioral insights. Contextualization of all the data from diverse demographics, temporal conditions, and platforms was achieved through real-world data. Preprocessing involved data cleaning, deduplication and min-max normalization. This was then followed by using TF-IDF for semantic feature extraction, and finally, contextual features were embedded into tensors. The proposed ESS-SLSTM model was employed for dynamic User-Application Interaction. Results indicated that the proposed ESS-SLSTM outscored CAPIR, BM25, and TF-IDF in terms of relevance, usefulness, and content adequacy. It also achieved Precision@5 (85.6 %), Recall (72.3%), and MAP (66.5%). It thus indeed proves to be an effective approach for contending with user intent and contextual relevance. The main drawbacks of this approach include complicated models and computational power. Future avenues may suggest exploring lightweight models for mobile deployment and real-time ad hoc adaptation to context changes from users.

References

[1] Abu-Rasheed, H., Weber, C., Zenkert, J., Dornhöfer, M., & Fathi, M. (2022, March). Transferrable framework based on knowledge graphs for generating explainable results in domain-specific, intelligent information retrieval. In Informatics (Vol. 9, No. 1, p. 6). *Multidisciplinary Digital Publishing Institute.* https://doi.org/10.3390/informatics9010006

[2] Ali, Z. (2017). Recent Advances in Nonvolatile Memory. *International Academic Journal of Science and Engineering, 4*(1), 163–175.

[3] Braun, A. (2021). Retrieval of digital elevation models from Sentinel-1 radar data–open applications, techniques, and limitations. *Open Geosciences, 13*(1), 532-569. https://doi.org/10.1515/geo-2020-0246.

[4] Boudjadar, J., Islam, S. U., & Buyya, R. (2025). Dynamic FPGA reconfiguration for scalable embedded artificial intelligence (AI): A co-design methodology for convolutional neural networks (CNN) acceleration. *Future Generation Computer Systems, 169,* 107777.

[5] Dalimunthe, K., &Hayadi, B. H. (2022). Information Text Retrieval UntukPencarian Data PenilaianMengacuPada Saran Dari PengunjungMenggunakan Vector Space Modelimplementasi. *Journal Computer Science and Information Technology (JCoInT), 3*(1), 73-79.

[6] El-Ansari, A., Beni-Hssane, A., Saadi, M., & El Fissaoui, M. (2021). PAPIR: privacy-aware personalized information

retrieval. *Journal of Ambient Intelligence and Humanized Computing*, *12*(10), 9891-9907. https://doi.org/10.1007/s12652-020-02736-y

[7] Gunalan, N., Kavin Kumar, R., Saravanan, B., Surya, S., & Saran Sujai, T. (2023). Investing Data Flow Issue by using Rayleigh Model in Cloud Computing. *International Academic Journal of Innovative Research, 10*(1), 8–13. https://doi.org/10.9756/IAJIR/V10I1/IAJIR1002

[8] Izacard, G., Caron, M., Hosseini, L., Riedel, S., Bojanowski, P., Joulin, A., & Grave, E. (2021). Unsupervised dense information retrieval with contrastive learning. *arXiv preprint arXiv:2112.09118.*

[9] Jeronymo, V., Bonifacio, L., Abonizio, H., Fadaee, M., Lotufo, R., Zavrel, J., & Nogueira, R. (2023). Inpars-v2: Large language models as efficient dataset generators for information retrieval. *arXiv preprint arXiv:2301.01820.*

[10] Rakesh, N., Mohan, B. A., Kumaran, U., Prakash, G. L., Arul, R., & Thirugnanasambandam, K. (2024). Machine learning-driven strategies for customer retention and financial improvement. *Archives for Technical Sciences, 2*(31), 269–283. https://doi.org/10.70102/afts.2024.1631.269

[11] Kumar, V., & Mehr, S. Y. (2024). Enhancing Electronic Design Automation Tools with an ML-Based Information Retrieval System. *International Journal of Intelligent Information Systems, 13*(3), 53-58.https://doi.org/10.11648/j.ijiis.20241303.12

[12] Lopez, I., Swaminathan, A., Vedula, K., Narayanan, S., Nateghi Haredasht, F., Ma, S. P., ... & Chen, J. H. (2025). Clinical entity augmented retrieval for clinical information extraction. *NPJ Digital Medicine, 8*(1), 45. https://doi.org/10.1038/s41746-024-01377-1

[13] Meesad, P. (2021). Thai fake news detection based on information retrieval, natural language processing and machine learning. *SN Computer Science, 2*(6), 425. https://doi.org/10.1007/s42979-021-00775-6.

[14] Mileva, A., & Tikvesanski, J. (2022). Hiding Data in a Switched Network. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 13*(3), 37-49. https://doi.org/10.22667/JOWUA.2022.09.30.037

[15] Pandey, S., & Sharma, S. (2023). A comparative study of retrieval-based and generative-based chatbots using deep learning and machine learning. *Healthcare Analytics, 3,* 100198. https://doi.org/10.1016/j.health.2023.100198

[16] Rateria, S., & Singh, S. (2024). Transparent, Low Resource, and Context-Aware Information Retrieval from a Closed Domain Knowledge Base. *IEEE Access, 12,* 44233-44243. https://doi.org/10.1109/ACCESS.2024.3380006

[17] Sansone, C., &Sperlí, G. (2022). Legal information retrieval systems: state-of-the-art and open issues. *Information Systems, 106,* 101967. https://doi.org/10.1016/j.is.2021.101967

[18] Shaik, A., Saxena, S., Gupta, M., & Parveen, N. (2024). Heterogeneous data-based information retrieval using a fine-tuned pre-trained BERT language model. *Multimedia Tools and Applications, 83*(21), 59537-59559.https://doi.org/10.1007/s11042-023-17868-4

[19] Singh, J. K. N., & Boursier, P. F. Adaptive Context-Aware Personalized Information Retrieval: Enhancing Precision with Evolutionary Machine Learning. *International Journal of Computer Applications, 975,* 8887.

[20] Tang, Q., Chen, J., Li, Z., Yu, B., Lu, Y., Yu, H., ...& Li, Y. (2024). Self-retrieval: End-to-end information retrieval with one large language model. *Advances in Neural Information Processing Systems, 37,* 63510-63533.

[21] Xiong, X., & Zheng, M. (2024). Integrating deep learning with symbolic reasoning in tinyllama for accurate information retrieval. https://doi.org/10.21203/rs.3.rs-3883562/v1

[22] Yang, C., & Singh, S. S. B. (2024). User Experience in Information System Platforms: A Study on Learning Styles and Academic Challenges. *Journal of Internet Services and Information Security, 14*(4), 209-223. https://doi.org/10.58346/JISIS.2024.I4.012