# Adaptive Context-Aware Personalized Information Retrieval: Enhancing Precision with Evolutionary Machine Learning

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## ABSTRACT
This study presents the Contextually Aware Personalized Information Retrieval (CAPIR) system. It is designed to address the limitations of traditional information retrieval (IR) models, which often rely on static keyword-based methods that neglect user context. CAPIR combines contextual awareness with evolutionary machine learning (EML), dynamically adapting to factors such as user behavior, location, and time. This approach improves the precision and relevance of search results by continuously refining retrieval strategies based on user interactions and feedback. Quantitative evaluation using precision, recall, and Mean Average Precision (MAP) showed significant improvements over traditional IR models, while qualitative feedback highlighted CAPIR's adaptability to evolving user needs. CAPIR's framework and experimental validation demonstrate its potential as a robust solution for environments requiring flexible and adaptive IR capabilities.

## General Terms
Information Retrieval, Machine Learning, Personalization, Contextual Awareness, Evolutionary Algorithms, Adaptive Systems

## Keywords
Contextually Aware Information Retrieval, Personalized Information Retrieval, Evolutionary Machine Learning, Precision and Recall, User-Centric Search Adaptation, Dynamic Search Refinement

## 1. INTRODUCTION
The rapid growth of digital information has increased the need for advanced information retrieval (IR) systems that address complex and evolving user needs [1, 2]. Traditional IR models, which rely on static keyword matching, often lack adaptability. This limitation leads to irrelevant search results and unsatisfactory user experiences [3]. Without contextual awareness or mechanisms to adjust to individual user preferences, these systems struggle to deliver results that align with the nuanced needs of modern users [4].

The Contextually Aware Personalized Information Retrieval (CAPIR) system was developed to overcome these challenges. It integrates evolutionary machine learning (EML) with personalized, context-aware retrieval capabilities. Unlike static IR models, CAPIR adapts its retrieval strategies in real time using feedback and user interactions. By continuously refining its methods through evolutionary algorithms, it aligns search outcomes with user preferences and context, evolving as user needs change [5, 6].

Existing IR systems often fail to integrate dynamic contextual changes and real-time user feedback effectively. Conventional machine learning approaches, while improving retrieval accuracy, remain static and unable to evolve alongside changing user behavior or preferences. The introduction of evolutionary algorithms in CAPIR addresses these limitations. Evolutionary algorithms iteratively optimize search strategies based on user interactions, enabling the system to adapt and deliver increasingly precise and relevant results. This adaptability is particularly important for environments where user contexts such as location, behavior and time changes continuously.

CAPIR's framework includes two core models for representing document-query relationships. The Term Vector Model (TVM) calculates similarity by evaluating the importance of terms within queries and documents. The Feature Vector Model (FVM) complements this by incorporating user-specific factors, such as past behaviors, preferences, and temporal relevance. By combining these models, CAPIR delivers search outcomes that are not only precise and relevant but also tailored to the user's unique context [7].

CAPIR's ability to address these gaps makes it particularly valuable for applications that require personalization and context-aware search solutions. These include dynamic environments such as digital libraries, e-commerce platforms, and recommendation systems, where user preferences and contexts evolve continuously. The main contributions of this paper include the development of CAPIR's framework, which integrates contextual awareness and evolutionary machine learning; a detailed evaluation of CAPIR using precision, recall, MAP metrics; and a demonstration of its effectiveness in delivering adaptive and personalized search outcomes.

This paper presents the development and assessment of CAPIR, highlighting its ability to dynamically adapt to changing environments. The goal is to enhance IR precision and relevance, establishing CAPIR as an effective solution for personalized, context-sensitive search experiences.

## 2. RELATED WORKS
The development of information retrieval (IR) systems has evolved significantly in response to the increasing complexity of user needs and the growing amount of digital information. This section reviews relevant literature in three key areas: contextual awareness in information retrieval, evolutionary machine learning approaches, and evaluation methods for personalized and adaptive IR systems. Together, these areas highlight the challenges and advancements in delivering dynamic, user-focused search results.

## 2.1 Contextual Awareness in Information Retrieval

Contextual awareness has become an important feature in modern IR systems, improving the relevance and precision of search results. Contextual factors such as location, device type, time of access, and user behavior play significant roles in determining what results are most relevant to a user [8]. By leveraging these factors, IR systems can refine the ranking of documents to align with real-time user needs.

For instance, spatial context, such as frequently accessed folders or specific file locations, can be used to prioritize documents from those folders, creating a more efficient and user-centric experience [6]. Similarly, temporal context, such as recently accessed or modified documents, allows systems to align results with immediate needs, ensuring that the most relevant information appears at the top [7].

User behavior, including interaction history and search patterns, further refines IR performance by predicting user preferences [9]. For example, systems can learn from frequently used queries or visited documents to anticipate future search requirements. Context-specific factors, such as whether a user is accessing information at work or home, or the type of device being used (mobile vs desktop), add another layer of relevance to search results [10, 11]. By integrating these contextual cues, IR systems can adapt dynamically to individual circumstances, significantly improving precision and user satisfaction.

## 2.2 Evolutionary Machine Learning in Information Retrieval

Traditional IR systems rely on static retrieval methods that fail to evolve with changing user needs, often producing irrelevant results when user preferences or contexts shift over time. To address these limitations, evolutionary machine learning (EML) combines evolutionary algorithms with machine learning techniques to create adaptive and dynamic retrieval systems [12-14]. Inspired by natural selection processes which are selection, crossover, and mutation, EML iteratively optimizes retrieval strategies based on user interactions and feedback. This continuous refinement ensures that the system adapts dynamically as user requirements evolve, delivering increasingly precise and relevant search results [10,15].

The functionality of EML is supported by two key models: The Term Vector Model (TVM) and the Feature Vector Model (FVM). The TVM represents documents and queries as vectors, where each dimension reflects the importance of terms. By measuring the similarity between query vectors and document vectors, the TVM enables effective ranking of results based on term relevance [16,17]. This model provides a foundation for matching queries with documents in a structured, measurable way.

In contrast, the Feature Vector Model (FVM) extends beyond simple term matching by incorporating additional user-specific factors, such as past behaviors, preferences, and temporal relevance. By including these contextual elements, the FVM develops a more nuanced understanding of the user's search context. This approach allows the system to prioritise results that better align with real-time user needs, significantly improving retrieval performance in dynamic environments [6,10].

EML's adaptability makes it particularly suitable for complex and dynamic search scenarios where static models often struggle to perform effectively. By continuously refining query and document representations, EML enables IR systems to align closely with evolving user behavior and contextual changes. This iterative process enhances both the precision and relevance of search results, ensuring that the system meets the demands of modern, personalized information retrieval [2,7].

## 2.3 Evaluation Methods for Personalized and Context-Aware IR

The evaluation of personalized and context-aware IR systems requires a combination of quantitative and qualitative methods to provide a comprehensive assessment. Traditional quantitative metrics such as precision, recall, and Mean Average Precision (MAP) are commonly used to measure retrieval accuracy and document ranking performance [2,12]. These metrics offer insights into the system's technical capabilities, such as its ability to retrieve and rank relevant documents effectively. However, they often fail to capture the advantages of real-time contextual adaptation and the variability of user preferences over time [9].

To address these limitations, user-centric evaluations are employed. Surveys, interviews, and feedback mechanisms allow researchers to gather qualitative data on aspects like usability, relevance, and user satisfaction. These evaluations provide a deeper understanding of how well the system adapts to individual preferences and changing contexts [18].

Comparative studies, where users interact with both static and context-aware IR systems, further validate system performance. For example, CAPIR's evaluation against traditional IR models demonstrates its ability to deliver dynamic and personalized results, reflecting real-world impacts on user experience [7]. By combining quantitative metrics with qualitative insights, researchers gain a holistic assessment of system adaptability and user-focused effectiveness.

The literature on contextual awareness, evolutionary machine learning, and evaluation methods demonstrates the growing need for adaptive and user-centric IR systems. While traditional models provide a foundational approach to document retrieval, they lack the flexibility to incorporate real-time contextual changes or dynamic user needs. Evolutionary machine learning, supported by models like TVM and FVM, offers a solution by enabling iterative adaptation of retrieval strategies. The evaluation of such systems requires both quantitative and qualitative methods to fully capture their technical and user-centric performance.

# 3. PROPOSED APPROACH

This section outlines the proposed Contextually Aware Personalized Information Retrieval (CAPIR) system. The approach addresses the limitations of traditional static IR systems by incorporating evolutionary algorithms and contextual awareness. CAPIR integrates dynamic feedback and user-specific factors to refine search outcomes iteratively, ensuring improved precision and relevance. The framework and evaluation process are detailed in the following sub-sections: CAPIR Framework and Experimental Setup.

## 3.1 CAPIR Framework

The increasing complexity of user search requirements highlights critical shortcomings in traditional IR systems, which rely heavily on static keyword-based matching. These systems often struggle to deliver relevant results in dynamic environments where user preferences, behaviors, and contexts evolve. Such limitations result in frequent mismatches between user intent and retrieved search results.

To address these gaps, CAPIR combines evolutionary machine learning (EML) with contextual awareness to create a personalized and adaptive IR framework. The proposed approach leverages evolutionary algorithms specifically selection, crossover, and mutation techniques to optimize search strategies in response to real-time user feedback and interactions. By dynamically adapting to user-specific contexts, CAPIR ensures that search results align closely with the user's current needs.

The CAPIR system integrates three primary components: Personalized Information Retrieval Systems (PIRS), Contextually Aware Information Retrieval Systems (CAIRS), and Genetic Algorithms (GA). These components work together to enhance search relevance. PIRS focuses on tailoring results by analyzing historical user data and behavioral patterns, while CAIRS adapts results based on factors such as location, time, and device type. Genetic algorithms enable continuous optimization, refining the system's performance iteratively through evolutionary processes.

The overall CAPIR framework (illustrated in Figure 1) provides a scalable and flexible solution for dynamic search environments. By merging personalization, contextual awareness, and evolutionary algorithms, CAPIR adapts to the evolving requirements of current users, ensuring search results remain precise, relevant, and timely.

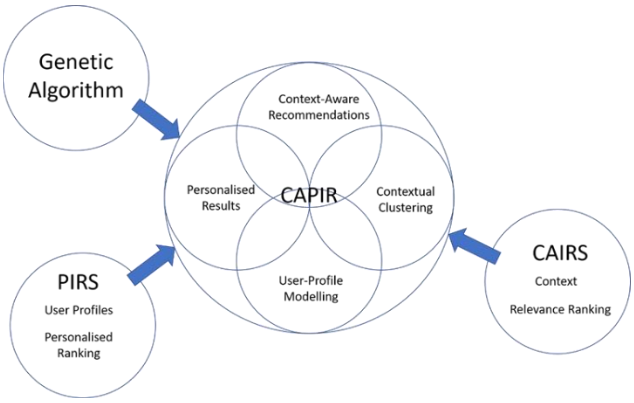


**Fig 1: Conceptual Framework for Contextually-Aware Personalized Information Retrieval (CAPIR)**

The CAPIR system employs an evolutionary machine learning (EML) model to continuously refine search results. CAPIR's adaptive framework incorporates evolutionary techniques such as selection, crossover, and mutation, which allow the system to evolve based on user interactions and feedback. These techniques enable CAPIR to adapt search strategies dynamically, ensuring relevance as user needs shift over time. CAPIR uses two primary models for representation: The Term Vector Model (TVM), which calculates similarity between queries and documents, and the Feature Vector Model (FVM), which includes user-specific elements like preferences and contextual information.

## 3.2 Experimental Setup

The CAPIR system was evaluated using a structured experimental setup designed to assess its effectiveness in delivering personalized and contextually relevant search results. To test CAPIR's performance, we used a mixed-method approach combining quantitative metrics with qualitative feedback from user testing. A corpus of 150 documents was used, spanning various topics and formats to reflect realistic search scenarios. Participants performed specific search tasks with CAPIR and a baseline traditional IR system, with performance measured in terms of precision, recall, and Mean Average Precision (MAP). These metrics were selected to provide a comprehensive view of CAPIR's ability to rank and retrieve relevant documents accurately.

In the proposed CAPIR model, pseudo-relevance feedback is used to get user's context for the calculation of document relevance and to determine the document ranking. In order to estimate the term weights, equation 1 is given below:

$$P(w|R) \approx P(w|Q) = \sum_{D \in M} P(w|D) \prod_{q \in Q} P(q|D) \qquad (1)$$

In the equation 1 above, the term weight distribution estimation $P(w|R) \approx P(w|Q)$, for the query $Q = \{q_1, \dots q_n\}$. Here it is supposed that $P(w|R)$ also generates a set of key terms in the top N documents $M = \{D_1, \dots qD_M\}$. It is apparent that a higher value of $P(w|Q)$ will result when the term $w$ is occurring most often in the document retrieval list, also co-occuring frequently with the query term $q \in Q$ in the document corpus $D$.

The main challenge in leveraging user profiles for contextual information retrieval lies in extracting relevant terms from documents and user profile tags. A simple computation, such as the similarity scores treats each document and the associated user tags as a bag-of-words (BOW) representation. This approach can be quite noisy in terms of similarity estimation. Firstly, user profiles contain varied information, and only certain aspects may be useful in the current context to meet users' information needs. Secondly, estimating similarities for long documents can result in noise. Therefore, focusing on contextually relevant parts of a document, rather than the entire document, may yield better similarity estimations and more accurate relevance judgments. This targeted approach helps in refining the search process and enhancing the overall effectiveness of information retrieval based on user context. With that, a factored relevance model to calculate the weighted distribution of the terms in the user profile is recommended, and use a term distribution $\theta_{U,q_U}$ to rank the documents in the current context, using $(l_U, q_U) \in (L, Q)$ where $l_U$ is the user's document title and $q_U$ are other attributes such as document type, and document date and time.

Next, to calculate the estimated relevance model based on the given user profile U, a set of tags are used as P=(D,T,r)∈U. Given that T' is a set of tags from the user's context, the union of all Ts from the set of use-assigned tags (D,T,r)∈U. The set of documents that are ranked at the top for this session provides a set of documents, with the user's search history. The equation 2 is given below:

$$P(w|\theta_{U,q_U}) = \sum_{(D,T,r) \in U} rP(w|D) \prod_{t \in T'} P(t|D) \qquad (2)$$

where estimated relevance model is able to get the semantic relationship between the user's specified tag keyword and the term that is presented in the documents, by the co-occurrence in the user's profile. Another relevance model $\theta_{U,q_U,l_U}$ is estimated by considering both the user profile $\theta_{U,q_U}$ estimated relevance with the set of top ranked documents shown as $M(\theta_U, q_U, l_U)$ where $M$ is the top ranked document retrieved by the system. This is provided in equation 3 below:

$$P\left(w \middle| \theta_{U,q_U,l_U}\right) = \sum_{d \in M(\theta_U, q_U, l_U)} P(w|D) \prod_{t \in \theta_{U,q_U}} P(t|d) \quad (3)$$

The equation 3 shows the factored relevance model where their estimation of $\theta_U, q_U, l_U$ needs to have $\theta_{U,q_U}$ to be estimated first, as it will act a factor model. Then, a linear combination of these two relevance models is used (Equation 2 and Equation 3) to create one combined equation 4:

$$P(w|\theta) = \gamma_H P(w|\theta_{U,q_U}) + (1 - \gamma_H) P\left(w\middle|\theta_{U,q_U,l_U}\right) \quad (4)$$

where $\gamma_H$ would be counted as the trade-off value to control the relativity of these two relevance models.

The CAPIR model requires estimating a total of three relevance models. First is the user profile relevance model, $\theta_{U,q_U}$ that will be estimated using the text that is in the user's preferences list. Next is to get the relevance of the documents in a given context, the value is obtained from $\theta_{U,q_U,l_U}$ using both the user's preferences and the top N retrieved documents, where the first value is treated as the query keywords and the second as the top retrieved relevant documents. Finally, both of the relevance models $\theta_{U,q_U}$ and $\theta_{U,q_U,l_U}$ are combined into a single relevance model $\theta$.

Qualitative feedback was collected through user-centric evaluations to complement the quantitative findings and assess CAPIR's real-world usability. After each experimental session, participants provided feedback through user feedback surveys, focusing on CAPIR's relevance rankings, intuitiveness, and responsiveness to contextual factors such as location, device type, and query evolution. Additionally, participant observations were conducted, where users interacted with CAPIR and compared its performance against traditional IR systems, with subjective responses recorded on the perceived relevance of results and system adaptability. To further understand CAPIR's effectiveness in meeting evolving user needs, structured interviews were carried out, encouraging participants to share detailed feedback on the system's ability to dynamically refine search results based on their preferences and contexts.

The proposed CAPIR approach integrates evolutionary machine learning with contextual awareness to address the limitations of traditional IR models. Through the combination of personalized and adaptive techniques, CAPIR enhances search relevance and precision, as demonstrated through the experimental setup. The next section will present the results and analysis of CAPIR's performance in comparison to baseline IR models.

## 4. RESULTS AND DISCUSSION

The CAPIR system's performance was evaluated using precision, recall, and Mean Average Precision (MAP) metrics. Table 1 shows CAPIR's results across multiple sessions, while Table 2 compares its performance with traditional IR systems like BM25 and TF-IDF. The results demonstrate CAPIR's ability to adapt dynamically and achieve superior precision and relevance.

### 4.1 Quantitative Performance Analysis

The CAPIR system's performance was evaluated using precision at 5 (P@5), recall, and Mean Average Precision (MAP) metrics across multiple experimental sessions. The results, summarised in Table 1, demonstrate CAPIR's ability to deliver precise and relevant search results, outperforming traditional IR systems.

**Table 1. Performance Metrics of CAPIR Across Experimental Sessions using Precision, Recall and MAP**

| Session | Precision at 5 (P@5) | Recall (R) | MAP |
|---|---|---|---|
| 1 | 0.714 | 0.368 | 0.332 |
| 2 | 0.692 | 0.562 | 0.450 |
| 3 | 0.813 | 0.778 | 0.385 |
| 4 | 0.846 | 0.675 | 0.626 |
| 5 | 0.700 | 0.562 | 0.591 |
| 6 | 0.684 | 0.493 | 0.567 |
| 7 | 0.615 | 0.526 | 0.591 |
| 8 | 0.706 | 0.433 | 0.567 |
| 9 | 0.571 | 0.216 | 0.000 |
| 10 | 0.818 | 0.493 | 0.216 |

From the table, it is evident that CAPIR demonstrated significant variation between P@5 and MAP across different sessions, reflecting how effectively relevant documents were ranked in the top results versus the overall list. The largest difference between P@5 and MAP occurred in Session 3, where CAPIR achieved a P@5 of 0.813 compared to a MAP of 0.385, indicating that while relevant documents were highly ranked in the top-5, their positions further down the ranking affected the overall MAP. Similarly, in Session 9, CAPIR's P@5 of 0.571 contrasted sharply with a MAP of 0.000, showing that while some relevant documents appeared in the top-5, their ranking was not aligned with the ground truth relevance.

In Session 10, a P@5 of 0.818 compared to a MAP of 0.216 highlights CAPIR's strength in retrieving relevant documents early in the ranking but also underscores room for improvement in ranking additional relevant documents further down the list. These differences reflect CAPIR's ability to prioritise relevant documents in the top ranks while highlighting areas where ranking optimisation could enhance overall retrieval performance.

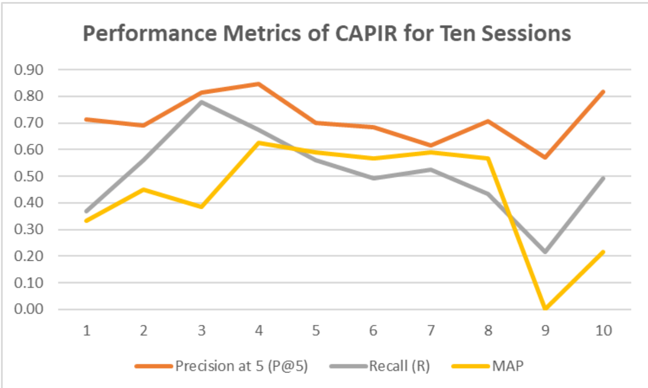


**Fig 2: Precision, Recall and MAP Scores for CAPIR**

In Session 9 (see Figure 2), however, the precision at 5 dropped to 0.571 and the MAP was 0.000. This result suggests that while some relevant documents appeared within the top results, CAPIR struggled to align retrieval outcomes with the ground truth relevance ranking. This discrepancy could be due to ambiguous or poorly formed queries, incomplete contextual inputs, or noise in the document corpus, which caused semantically unrelated documents to interfere with relevance ranking. While CAPIR mitigates these challenges in most sessions, this result underscores the need for refining query alignment and improving contextual acquisition mechanisms to further enhance robustness.

Additionally, noise in the document corpus may have played a role, where documents with similar but semantically unrelated content interfered with precision. Such scenarios highlight the challenges of balancing relevance and contextual cues in dynamic IR systems. CAPIR's reliance on contextual and personalized factors means that incomplete or ambiguous inputs can negatively affect retrieval outcomes. Session 9's results reflect common real-world challenges in information retrieval systems, such as handling ambiguous queries or incomplete contextual data. While CAPIR's dynamic framework mitigates these issues in most scenarios, further refinement of context acquisition and query alignment mechanisms can enhance robustness.

## 4.2 Comparison with Traditional Methods

To further assess CAPIR's effectiveness, its performance was compared against two traditional IR models—BM25 and TF-IDF. Table 2 shows that CAPIR achieved significantly higher MAP scores, indicating better ranking performance and retrieval precision.

**Table 2. Comparison of CAPIR with Traditional IR Methods (BM25 and TF-IDF) on Precision**

| Method | Precision @ 5(%) | Recall (%) | MAP (%) |
|---|---|---|---|
| CAPIR | **63.0** | **62.4** | **58.7** |
| BM25 | 47.3 | 54.1 | 50.2 |
| TF-IDF | 44.8 | 52.7 | 48.5 |

CAPIR's MAP score of **58.7%** significantly outperformed BM25 (50.2%) and TF-IDF (48.5%), demonstrating the system's ability to iteratively optimize retrieval outcomes through evolutionary machine learning while leveraging real-time contextual signals, such as location and temporal relevance. CAPIR's integration of evolutionary learning enables it to adapt retrieval strategies iteratively based on user feedback and contextual cues. This contrasts with traditional methods like BM25 and TF-IDF, which rely on static term-weighting schemes and cannot incorporate dynamic user contexts or evolving preferences

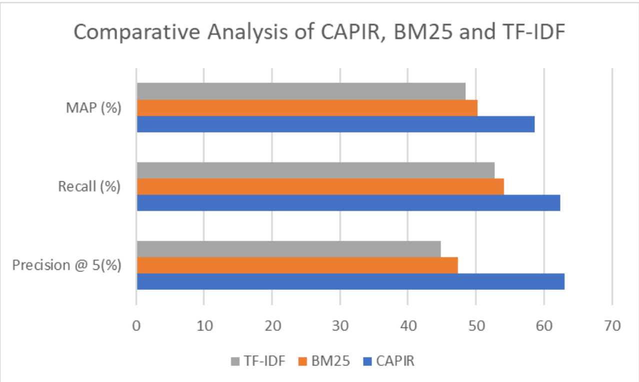


**Fig 3: Comparative Analysis of CAPIR, BM25 and TF-IDF**

CAPIR's performance improvements can be attributed to its integration of evolutionary machine learning (EML) and contextual factors. The adaptive nature of CAPIR allows it to iteratively refine search strategies by leveraging real-time user feedback, aligning search results more closely with user preferences and evolving contexts. Unlike static models, which operate on predefined retrieval logic, CAPIR continuously adjusts its ranking and relevance strategies to suit dynamic search requirements.

The system demonstrated notable success in Sessions 3, 9 and 10, where user queries exhibited significant contextual variation. In these sessions, CAPIR outperformed baseline models by effectively adapting its retrieval strategies in response to shifting user intents and contexts. For example, spatial and temporal factors played an essential role in these sessions, enabling CAPIR to prioritise documents accessed in specific folders or those with recent modifications. This contextual integration allowed CAPIR to deliver precise results even when user queries were ambiguous or complex. Conversely, the challenges observed in Session 9 reveal areas for future improvement. While CAPIR's framework is designed to handle noisy or incomplete inputs, ambiguous queries and contextual gaps can impact its ability to deliver optimal results. Future enhancements to CAPIR could focus on refining query alignment strategies, improving noise reduction techniques, and enhancing the extraction of contextual cues from incomplete inputs.

Furthermore, CAPIR's ability to incorporate spatial and temporal contexts provided a distinct advantage over traditional IR models like BM25 and TF-IDF. While traditional models rely solely on term-based similarity, CAPIR dynamically adjusts search results based on contextual signals such as the time of access, user location, and device type. By integrating these cues, CAPIR ensures that results are more relevant and aligned with real-world user needs. For instance, prioritising documents modified recently or accessed on a specific device enhances search precision in time-sensitive tasks.

Qualitative evaluations reinforced the quantitative findings, highlighting CAPIR's real-world effectiveness and advantages over traditional methods. Participants expressed a strong preference for CAPIR's adaptive framework, noting its ability to deliver relevance rankings that felt more intuitive and aligned with their intent. CAPIR's responsiveness to contextual elements such as location, device type, temporal factors, and access patterns was frequently cited as a key factor in meeting users' search expectations. In contrast, traditional models, which rely on rigid, context-independent approaches, often failed to address the dynamic needs of users. This user-centric adaptability underscores CAPIR's design objectives of providing personalized, context-sensitive, and effective search outcomes.

This qualitative feedback aligns with CAPIR's design objectives of creating a personalized and context-sensitive search experience. CAPIR's adaptive framework allowed it to handle diverse search tasks effectively, making it better suited for real-world, dynamic environments where user contexts evolve continuously.

The combination of CAPIR's superior precision, recall, and MAP metrics, along with positive user feedback, underscores its effectiveness. These results demonstrate that CAPIR offers a significant advancement over traditional IR models, positioning it as a scalable and adaptable solution for complex information retrieval needs.

# 5. CONCLUSION

This paper introduced the Contextually Aware Personalized Information Retrieval (CAPIR) system, an adaptive framework that integrates evolutionary machine learning (EML) and contextual awareness to overcome the limitations of traditional IR models. CAPIR dynamically refines search strategies based on real-time user feedback and contextual signals such as location, device type, and behavioral preferences. The experimental results demonstrated CAPIR's significant improvements in precision, recall, and Mean Average Precision (MAP), outperforming traditional models like BM25 and TF-IDF. Qualitative evaluations further validated CAPIR's user-centric adaptability, with participants reporting more intuitive and relevant search outcomes.

The success of CAPIR highlights its potential as a robust and scalable solution for modern information retrieval challenges. Future work will focus on enhancing scalability to manage large-scale datasets efficiently and integrating advanced deep learning techniques to further improve query understanding and retrieval performance. Exploring richer contextual signals, such as sentiment analysis and social interactions, will refine CAPIR's personalisation capabilities. Additionally, expanding CAPIR's applications to fields like medical, educational, and legal document retrieval will demonstrate its versatility in addressing domain-specific challenges. By aligning search results with evolving user needs and dynamic contexts, CAPIR represents a significant step forward in delivering adaptive, effective, and personalized search experiences.

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