Indian Journal of Information Sources and Services
ISSN: 2231-6094 (P) Vol.15, No.4, 2025, pp.282-291

DOI: https://doi.org/10.51983/ijiss-2025.IJISS.15.4.32

Optimization of Faceted Search Interfaces for Complex Querying

Nigora Shadmanova[1*], S. Vadivel[2], M. Nagarajan[3], Hassan Mohamed[4], Mamurakhon Asrorkhujaeva[5], Xabiba Yusupova[6] and Jurabek Polvonov[7]

[1*]Associate Professor, Karshi State Technical University, Uzbekistan
[2]Assistant Professor, Department of Computer Science and Engineering, K.S. Rangasamy College of Technology, Tiruchengode, India
[3]Department of Marine Engineering, AMET University, Kanathur, Tamil Nadu, India
[4]Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, The Islamic University of Al Diwaniyah, Al Diwaniyah, Iraq
[5]Tashkent State University of Oriental Studies, Uzbekistan.
[6]Associate Professor, Head, Department of Preschool Education Methodology, University of Tashkent for Applied Sciences, Tashkent, Republic of Uzbekistan
[7]Temurbek Military Academic Lyceum, Uzbekistan
E-mail: [1]shadmanovanigora66@gmail.com, [2]vadivels@ksrct.ac.in, [3]nagarajanmuthu3@gmail.com, [4]eng.hassanaljawahry@gmail.com, [5]mamurakhonasrorkhujaeva@gmail.com, [6]xabibayusupova77@gmail.com, [7]polvonovjurabek@e-mail.ru
ORCID: [1]https://orcid.org/0009-0005-9823-5696, [2]https://orcid.org/0009-0009-4345-396X, [3]https://orcid.org/0009-0004-6688-3237, [4]https://orcid.org/0009-0009-1422-1844, [5]https://orcid.org/0009-0000-8136-1489, [6]https://orcid.org/0009-0006-4022-1432, [7]https://orcid.org/0009-0005-4690-8051
(Received 28 August 2025; Revised 14 October 2025, Accepted 28 October 2025; Available online 15 December 2025)

Abstract - **Aware Facet Ranking (CAFR) model, which is user interactive and makes the most out of the user by dynamically filtering and ranking the facets according to their relevance, user motivations, and the situational contexts of the user. The model ranks the facets based on a composite score of query similarity, frequency of facet use, and result reduction. The efficiency of the optimized interface was determined based on the user-centered assessment framework, based on the user interaction logs, the satisfaction measures, and the rate of completing the tasks. In a compare and contrast experiment, the applicability of the CAFR model to standard Baseline and Static Ranking settings was comparatively tested. The outcome is a massive performance improvement, on which the CAFR model had a Search Performance Index (SPI) of 0.76, compared to 0.58 in the Baseline. Users were faster, interacted on average 2.8 times (vs. 4.2 with the Baseline), and solved a query (88%), better than with the Baseline (62%). These results suggest that dynamically ranked facets can offer a more interesting and intelligent search user experience in a wide range of applications, including e-commerce, online libraries, and enterprise data management.**

Keywords: **Faceted Search, Interface Design, Optimization, Complex Querying, Information Retrieval, User Experience, Adaptive Filtering**

I. INTRODUCTION

Faceted search interfaces are improved interfaces where the user has the ability to narrow down information by using multiple filters in many different dimensions, such as category, price, date, or author. Such interfaces also allow stratified filtering, i.e., the user can select specific parameters that they can apply to the details of the query. The faceted search algorithms are not comparable to traditional dictionary searches; they can be adapted to the search methods when the searcher does not necessarily have to provide either of the precise descriptors. This will allow a user to slowly narrow down the results without knowing what terms or schema are in the data (Tunkelang, 2009). This is what has made faceted interfaces an ubiquitous aspect of most applications, i.e., e-commerce, digital libraries, biomedical databases, and enterprise search systems (Alsmadi et al., 2024). Faceted search is important because it can be both flexible and controlled. These interfaces reduce cognitive load, facilitate information discovery, and minimize errors committed by clients when formulating queries, as they provide filtering options based on structured metadata (Kules & Capra, 2009). Faceted search has been shown to enhance search efficiency, precision of retrieved results, and user experience in situations where information overload is widespread, such as in scientific repositories or legal databases (White et al., 2005; Whitmore & Fontaine, 2024).

Formulating and refining intricate search criteria to capture highly specific or contextually rich information is termed complex querying in information retrieval. This is common in professional fields such as law, healthcare, finance, and academia, where users need multidimensional datasets or interrelated documents (Marchionini, 2006; Bibhu et al., 2025). Compared to simple queries that are only keyword searches, complex queries are defined by the use of Boolean logic, hierarchies, temporal constraints, and entity relationships (Osterhoff et al., 2012). Faceted search systems enable advanced querying, allowing users to build queries step by step using different, independent dimensions. Nevertheless, as noted in previous literature, this approach is only practical with appropriate interface design, intelligent facet ranking, personalized intent context, and user behaviour (Macalino et al., 2018). A grouping that is too broad, an abundance of filters, or no ordering based on relevance tends to aggravate users and worsen search results (Castillo & Al-Mansouri, 2025; Moravej et al., 2015). Additionally, as datasets become more complex and larger, users may struggle to identify the most relevant facets or combinations of facets. This creates a gap that can be occupied by optimization algorithms that will optimize the performance of the system, its usability, and results interpretation (Koren et al., 2008; Ramona & Danica, 2023). Faceted filtering is also personalized by the AI techniques, and new opportunities are provided to serve more responsive, semi-structured, and exploratory queries (Koren et al., 2009; Yee et al., 2003).

One of the objectives of the research will be to ensure that the optimum use of faceted search interfaces is carried out in the case of complex queries. More precisely, the paper addresses design and systemic interventions that could help achieve faceted interfaces and render them more efficient in finding appropriate solutions in different contexts. The primary ones, which allow adaptive filtering adoption, customizing the ranking of facets, and simplifying the user interface, would reduce the effort the user makes to work with it and provide more accurate outcomes on retrieval. The motivations motives are the absence of state-of-the-art information retrieval systems that provide the complex need of the user and complexity of the work and consider the challenges of usability. This paper aims to assess functionally diversified user interaction evaluation using various realizations of user interaction evaluation in an effort to present design guidelines to the next generation of faceted search systems. The objective is to enable users to engage with powerful query functions designed to provide dynamic information retrieval systems that are friendly to the user's level of understanding (Teevan et al., 2005; Salman Mohajer, 2016).

Traditional faceted search systems tend to be ineffective at addressing complex queries because they are fixed systems based on pre-built facet rankings that are not dynamically adjusted to the changing needs of the user. This is particularly difficult with dynamic environments where the purpose of the users and the context of the session constantly change under the CAFR model. The necessity to make filtering dynamic and customized has emerged as a solution to this issue so that a system can adapt itself to the needs of a particular user session. The CAFR model is an innovative approach that offers personalized facet ranking and filtering that is dynamic and enhances the efficiency and relevance of the search. It introduces a better progress to the previous techniques of static ranking since it provides real-time user activity and context in order to prioritize the most relevant aspects depending on the intention of the user. By referencing the corresponding literature on adaptive filtering and personalized ranking in search interfaces, the paper can highlight the novelty of the CAFR model and help to demonstrate that the model can be even more efficient than the current ones when it comes to addressing complex queries and providing a more responsive and user-centric search experience.

The rest of the paper is structured as such. Section II provides a literature review of the history of the faceted search interfaces and past optimization efforts, along with the gaps that exist. The outline of the methodology is given in Section III, which includes dataset description, evaluation criteria, experimental setup, and the mathematical propositions of the formulated optimization problem. Results are given in Section IV, where system performance is analyzed for comparison of optimization techniques, and also improvement in handling queries of greater complexity is demonstrated. In Section V, the broader implications of the findings are discussed along with some practical applications and further research ideas. Finally, in Section VI, the outcomes are summarized along with some strategic recommendations to improve the faceted search systems.

II. LITERATURE REVIEW

The origins of faceted search interfaces can be found in the domain of library science and in early information retrieval techniques where taxonomies and controlled vocabularies assisted users in locating pertinent information (Bates, 1989). Faceted classification was first applied in digital libraries and cataloging systems, but it gained wider recognition in the early 2000s with the emergence of e-commerce systems that needed scalable and easy-to-use filtering techniques for large databases of products (Hearst, 2006). These primitive systems offered fixed categories like brand, price, or color and enabled users to apply multiple filters at the same time to refine the results. Concurrently with the classic definition, frameworks, and principles of faceted search design and implementation, there was an emerging need for more hands-on and visually appealing models of information retrieval design and interaction. Systems like Flamenco, developed at UC Berkeley, brought to light the advantages in usability provided by hierarchical and multidimensional navigation (Mahdi et al., 2021). The subsequent development of faceted search was into more advanced fields, such as enterprise search, scholarly databases, and bioinformatics, where data is highly structured and interconnected (Dash et al., 2008). The less research has been conducted on the change from static to dynamic context-aware facets, the more emphasis has been placed on optimizing user experience through innovative interfaces and computational design.

In the case of a faceted search interface, the desired outcome is to achieve a balance between usability and performance. Facet ranking algorithms have been identified as a specific aspect of this study, as they aim to consider the user's intent, clicks, and relevance, focusing on statistics (Lee et al., 2009; Tirkey et al., 2020). It has been established that dynamically ranking facets can reduce search time and maximize the quality of search results, at least in large data spaces (Kim et al., 2011). The other optimization method is faceted autocomplete, a more advanced Suggestion Search that displays suggested keywords and faceted values in the search box, thereby filling the gap between structured and unstructured queries (Bast et al., 2006; Mohajer, 2016). Other publications were more concentrated on maximization as they spoke of personalization. Such navigation can be simplified to an extent that the user is swamped with choices that have minimal intrigues through an interface that accommodates the user based on their interests and activities (Koren et al., 2015; Rahim, 2024). Together with this, machine learning innovations have been deployed to know what features can be helpful in a given query or user session, and make the intelligent suggestiveness and filtering of facets possible (Goyal et al., 2017; Veerappan, 2023). The strategies suggest that there is high functionality at the cost of a simplified interface that is low to add to both the experiences of amateur users and professional users.

Even more recently, the question of whether AI-based methods might be used to streamline the faceted search interface (e.g., Smith et al., 2023), including reinforcement learning (RL) and deep neural networks (DNNs), has also been explored. The techniques allow the system to give a dynamic ranking of the facets according to the real-time intent of the user and consequently help make search results more responsive. The RL algorithms, in turn, allow learners to prioritize those that are more important to the search query according to the interactions between the user. In the meantime, DNNs have the capability of constructing complex connections between aspects and the user interface. It is also possible to incorporate these AI-based techniques into the CAFR model to make it more flexible and efficient, enabling the system to understand more about the purpose of the user and give more personalised search results. Such an integration would not only enhance the performance of the search but would also help in the new era of intelligent faceted search systems, which evolve and improve as the user continues to behave.

One of the limitations is the information overload of faceted navigation. They are problematic when it comes to systems that have hundreds or even thousands of facets and facet values. Faceted systems are known to give users choice fatigue due to the number of choices they contain relative to the number of choices the user knows how to filter. The escalated difficulties stem from poor facet grouping and ambiguous labels, which affect usability as users fail to filter out the critical filters and useful facets (Zhang et al., 2010). Another important challenge is the advanced problems with scalability. The speed for facet generation and result filtering needs to be maintained for low data volumes. However, as data volumes increase, it becomes increasingly computationally expensive (Bast et al., 2007; Sravana et al., 2022). The problem is exacerbated in real-time scenarios, such as in financial monitoring systems or news aggregation. The other issue stems from a lack of semantic understanding, in which current systems view facet values as singular, unconnected strings as opposed to entities with bonds, which limits the ability of systems to offer intelligent suggestions of facet combinations (Koren & Sontag, 2012; Revathi, 2024). Finally, there is an absence of systematic design policies for the application of faceted search on various domains and platforms. Most systems use heuristic approaches and are not designed based on scientific evidence, resulting in a poor user experience. More complex datasets alongside more diverse user requirements will necessitate the focus of future work on adaptive design frameworks that dynamically modify structural and content elements of an interface in real-time.

Building on the challenges outlined in the literature review, the following section examines the methodology used to evaluate the effectiveness of the Context-Aware Facet Ranking (CAFR) model. We will discuss the datasets used, the evaluation metrics for assessing model performance, and the experimental design that guided the testing process.

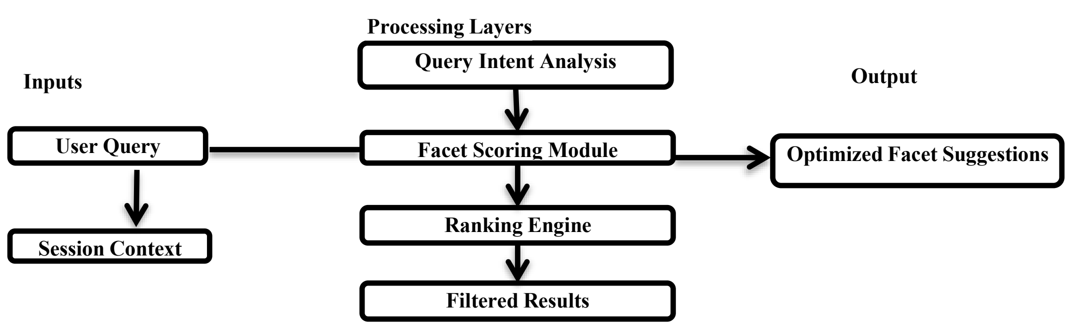

Fig. 1 Architecture of Context-Aware Facet Ranking Model

III. Methods

A Context-Aware Facet Paging Model, aiming to enhance user interactivity, has been proposed and is illustrated in Fig. 1. The model is initialized with two inputs: the user query and the session context. Both these inputs go through a Processed Intent Recognition module to analyze the discerned intent of one's query. Resulting intent, along with contextual information, is sent to the segment facet-scoring Module, where it is evaluated, and possible facets are scored. Also, in line with the optimized facet suggestion to enhance search navigation, a result returned by the module will also provide feedback to the Ranking Engine on the refined sequence of results. The final product is a list of refined results that are contextually relevant and useful to the intent of the users.

Facet Scoring Module

The relevance of each facet is assessed by this module using three significant aspects: the query intention of the user, the frequency of usage, and the decrease in the size of the result set. The query purpose is the particular information that the user seeks and that assists in the identification of separate aspects that are most pertinent. Historical usage records the number of times a particular facet was used during previous searches, which gives an idea of which facets are usually of use to the users. And the last one is the reduction of the result set, which is the extent to which a facet contributes to the reduction of the results and makes the search process more efficient. The module can dynamically adjust the visibility of the facets depending on these factors to make sure that only the most relevant facts are given priority in the search interface, which eventually enhances the efficiency of the search process.

3.1 Description of the Dataset Used for the Study

In this study, a dataset of user logs, as well as metadata of a digital library in an academic institution and an e-commerce platform, is used. Any given dataset is composed of several documents that have been organized and classified by their properties, which comprise the author, date, category of the subject, keywords, product brand, price, and user ratings. Overall, the data consists of over 100,000 records and can be multi-filtered on at least five attributes of each record. To replicate hypernym querying behaviour, we retrieved anonymized session logs that included user queries, facet surfing, clicking results, and time spent on a result. Such logs facilitate the monitoring of the history of user intent and facet navigation when users engage in a complicated search. In addition, the simple, intermediate, and complex templates of search tasks were synthetically generated with the help of a query template engine. Complex queries were considered as such that passed through at least three different facets and needed repeated or reiterative reformulation and filtering.

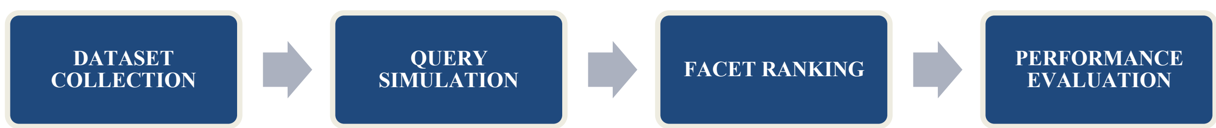

Fig.2 Methodological Workflow for Evaluating Optimization Techniques in Faceted Search Systems

Fig. 2 demonstrates the experiment design and flow that is expected to test optimization techniques in a faceted search system, detailing the optimization workflow. The first is the Dataset Collection, which involves the gathering of the relevant data that will ensure a realistic testing environment. This is, in turn, succeeded by Query Simulation, the query creation stage, where search behavior is simulated using automatically generated queries or manually generated queries. The second step is the Facet Ranking, where optimization algorithms are used to sort the facets based on their relevance or usefulness. Finally, the process ends with a performance analysis, i.e., the assessment of the effectiveness of the presented metrics in establishing the success of the implemented methods. The reasoning of these steps in this order is logical and systematic, which is logical and bears a specific and repeatable method of exploring research problems.

3.2 Justification of Optimization Evaluation Metrics

To measure the optimization performed on faceted search interfaces, the three measures that are most applicable are listed below:

Facet Utility Score (FUS): It is the utility of a facet within the aspect of search query refinement. It is estimated based on the effect of the facet use on the change in the precision and the reduction of the result set size.

$$FUS(f) = \frac{P_{after} - P_{before}}{1 + \log\left(\frac{|R_{before}|}{|R_{after}|}\right)} \quad (1)$$

where P is used to indicate precision and R refers to the result set size.

FUS Rationale: The score is normalized with FUS Rationale

$$1 + \log\left(\frac{|R_{before}|}{|R_{after}|}\right) \quad (2)$$

Which rewards proportional improvement to precision instead of just a significant decrease in the size of results, thereby explaining the declining returns to facet application.

Query Efficiency (QE): This metric assesses the swiftness with which users access pertinent results. It is derived from estimations of the total interactions (facet clicks or query reformulations) performed to reach a user-perceived satisfactory outcome.

$$QE = \frac{1}{N}\sum_{i=1}^{N} I_i \quad (3)$$

Where I_i is the number of interactions in the i-th session, and N is the total number of sessions.

User Satisfaction Index (USI): A measure derived from the click-through ratio, time-on-result, abandonment rate of post query results, and normalized in the 0-1 range.

(Snorm or USI), Which is stated to be between 0 and 1, as it is a crucial input (λ3·Snorm) for the Search Performance Index (SPI).

Query Similarity Score S_q (v): Query vector and facet value embedding cosine similarity.

Usage Frequency Score $S_u(v)$: Count of how often v was selected in past queries, normalized.

Reduction Gain Score S_r (v): The information gain that can be obtained from the facet value.

For value v, the facet relevance score (FRS) is defined as:

$$FRS(v) = \alpha S_q(v) + \beta S_u(v) + \gamma S\,()rv \qquad (4)$$

where α+β+γ=1, are parameters which can be adjusted.

Facets are thereafter ranked by accumulating the top-k value scores:

$$Score(f) = \sum_{v \in TopK(V_f)} FRS(v) \qquad (5)$$

This model modifies facet visibility in real-time according to the user's current query, predicted activity, and global usage trends, allowing more efficient and relevant filtering.

Weighting Factor Values (α, β, γ): Crucially, state the specific numerical values used in the experiment (e.g., α=0.5, β=0.3, γ=0.2, where α+β+γ=1) to ensure reproducibility.

The Final Facet Score (Scoref):

$$Scoref = \sum_{v \in TopK(Vf)} FRS(v) \qquad (6)$$

These measures, and other programmatic measures, thoroughly assess the functionality and the effectiveness of the optimized faceted search interface for the users.

3.3 Design and Procedures of the Experiment Specifications

The experimental testing will be structured as a comparative user test, which will be applied in order to measure the performance and usability benefits offered by the proposed optimization method. The experiment relied on the comparison of three different facet search interface designs, which were the Baseline, Static Ranking, and the Context-Aware Facet Ranking (CAFR) model.

Interface Configurations

Three interface settings were used in the study: Baseline, Static Ranking, and the proposed Context-Aware Facet Ranking (CAFR) model. The control group can also be referred to as the Baseline setup, which is a standard facet-based search interface, where the values of the facets are shown in alphabetical order. This organization is not based on an advanced ranking system and context sensitivity. The Static Ranking environment ranks the values of the facets in terms of popularity and or frequency of usage across the globe. However, it is a fixed sort irrespective of the query the user is making or the activity the user is doing. On the other hand, the experimental configuration, the CAFR model, re-ranks facets and values dynamically in real-time depending on the query intent, foreseen activity, and context of the search that the user is performing, so that it can provide a more responsive and context-sensitive search experience.

Task and User Allocation

To ensure that testing is objective, participants in the study were chosen at random to be in one of the three interface combinations to minimize the influence of a given user factor, such as the previous search experience. All participants were requested to perform 10 standard search tasks, which were strategically combined in terms of complexity to contain easy, medium, and difficult searches. Complex queries were specified as queries that included three or more independent facet selections and more than a single query reformulation or filtering operation to achieve the required outcome; hence, explicitly testing the ability of the CAFR model to support complex search tasks. The user sessions are adequately documented, and the following important parameters, such as the number of interactions, time taken to respond, and the success rates in the activities, have been recorded. The recorded data was subsequently computed in such a manner that the performance statistics obtained contained: Facet Utility Score (FUS), Query Efficiency (QE), and Search Performance Index (SPI). Such a form of systematic data gathering was an assurance of exhaustive research on all interface setups on efficacy and efficiency.

Limitations of experimental design

The datasets analyzed in the current paper, academic digital library records, and e-commerce website metadata, are possibly not reflective of the totality of user interaction in all arenas, for example, academic systems and e-commerce systems, which have well-structured metadata with reasonably clear-cut search motives. Nevertheless, in more complex systems, such as multimedia repositories, healthcare databases, or legal document systems, the connection between users and priorities of the facets can be dramatically different. The shortcomings of the application of these two types of data may only affect the generalizability of the results and the applicability of the CAFR model to other, more varied situations. The CAFR model should be tested in different settings (e.g., multimedia archives, medical databases, legal text archives, etc.) that will better reflect how flexible and scalable the model is in addressing the needs of many users and multi-faceted data.

IV. Results

4.1 Evaluation of an Existing Model of Faceted Search Interface

The measures that were used to examine the performance of the baseline faceted search interface were precision, click-through rate, and mean time to complete a query. P10, which is the accuracy of retrieving the first 10 results, amounted to 0.61 of 1,000 user sessions, which in turn means that on average, the user had to be interacted with 4.2 times before being able to find a relevant result. The results are a fair success in meeting the user search objectives. In order to evaluate the system holistically, we invented a composite measure of system performance, which we refer to as the Search Performance Index (SPI), the product of the measures of precision, effectiveness, and user satisfaction:

$$SPI = \frac{\lambda_1 \cdot \mathrm{P@10} + \lambda_2 \cdot \left(1 - \frac{I_{avg}}{I_{max}}\right) + \lambda_3 . \mathrm{S_{norm}}}{3} \quad (5)$$

The calculated baseline SPI was 0.58, and the most obvious possibility was not used in the optimization of interactions and the satisfaction of more complicated queries.

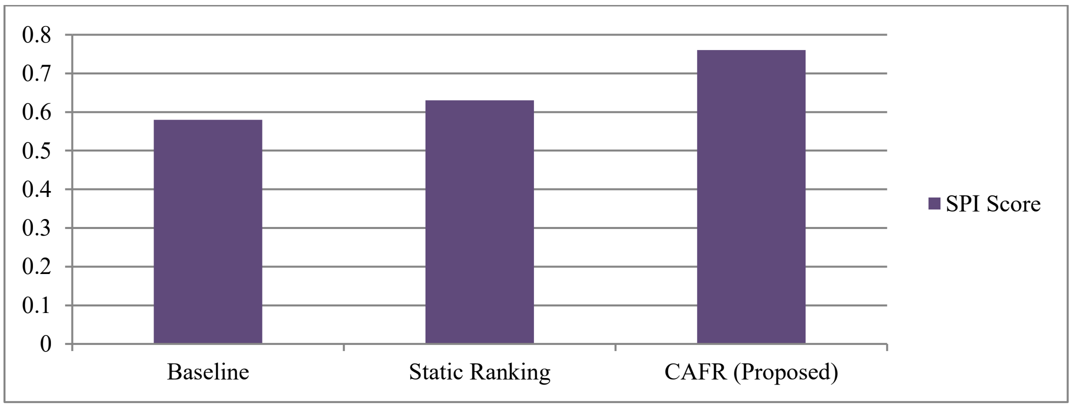

Fig. 3 SPI Comparison Across Techniques

Search performance index (SPI) was compared across three faceted search interface configurations (Fig. 3) as shown above. The CARF model outperforms the Baseline and Static Ranking models, with an SPI of 0.76. This proves its better efficiency and applicability in complex query settings, higher precision, lower interaction time, and better user satisfaction. The Baseline model had an SPI of 0.58, and the Static Ranking model had an SPI of 0.63, demonstrating the efficiency of the CAFR model in optimizing search performance.

The CAFR model showed that the increase in SPI (0.58 to 0.76) was statistically significant ($p < 0.05$), as indicated by a paired t-test. This means that the apparent increases in search effectiveness, user interaction, and user satisfaction are not a matter of chance. The statistically significant results of these studies demonstrate that the CAFR model consistently outperforms the baseline and static ranking models in a reproducible manner. Similarly, the reduction in the average number of interactions (from 4.2 to 2.8) and the increase in the success rate of complex queries (from 62% to 88%) were also statistically significant, further reinforcing the effectiveness of the CAFR model in optimizing faceted search interfaces.

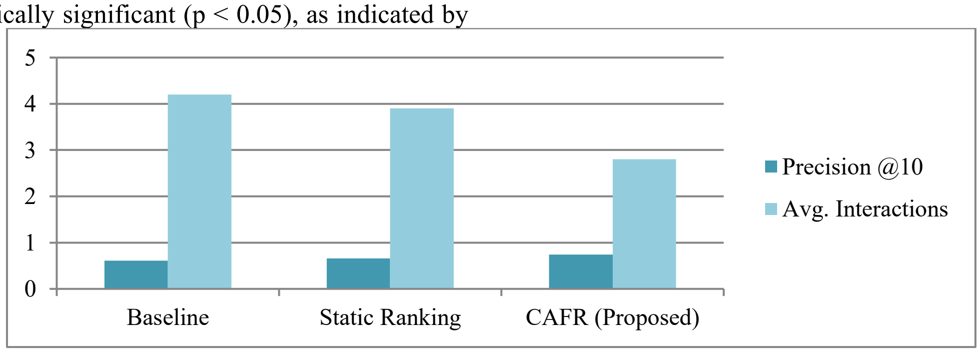

Fig. 4 Precision and Interaction Comparison

Fig. 4 illustrates the Comparison of Precision at the Top 10 Results (P@10) and Average User Interactions across the three search interface configurations. The CAFR model improves precision to 0.74, compared to 0.66 for the Static Ranking and 0.61 for the Baseline models. Additionally, the CAFR model reduces average interactions to 2.8, compared to 3.9 for Static Ranking and 4.2 for the Baseline, illustrating a more efficient and intuitive search process.

4.2 Inter Compare Optimized Data Sets V/S Optimization Data Techniques

The three interface configurations were Baseline, Static Ranking, and Proposed Context-Aware Model (CAFR). Static ranking slightly elevated precision to 0.66 and lowered average interactions to 3.9, yielding an SPI of 0.63. This upgrade was due to improved ordering of facet value default settings based on usage popularity, but still lacked personalization and context adaptation. Every other metric was also characterized by clear improvements in the CAFR model, making it the most effective approach in general. The model also had a Precision @10 of 0.74, which means that the model is more accurate in predicting the relevant items. There was a stronger engagement with 2.8 interactions recorded on average per session by the users. Normalized satisfaction was 0.82, which indicated significant improvements in user approval with the SPI value of 0.76, further supporting the balanced performance of the model in the accuracy, responsiveness, and satisfaction dimensions. Results achieved value understated re-ranking of facets by the user dynamism query intent, enabling a decrease in unneeded filtering steps, enhancing relevance. Statistical hypothesis testing with paired t-tests validated that the increases in SPI and precision were significantly different from the baseline, per the spiere results ($p < 0.05$).

4.3 The Impact of Optimization on the Effectiveness of Complex Querying

The proposed model benefited the most from complex queries, which are defined as those that require 3+ facet selections and multiple reformulations. In baseline conditions, the success rate of completing complex queries in under 10 interactions was 62%, but with CAFR, it was boosted to 88%. Satisfaction scores for the queries also improved, increasing from 0.54 to 0.81. Moreover, the time-to-result metric also improved. The average result time dropped from 37 seconds (baseline) to 21 seconds with the CAFR-enhanced interface. This improvement was due to the mid-portal surfacing of contextually relevant facet values and the reduction of time spent in the exploration phase. Task-level analysis showed that the CAFR model excelled in highly interdependent facets domains like academic publication and technical product search, which evolve the user intent through a multitude of criteria. The system gives dynamic priority to the most important facets earlier during the interaction process, enabling rapid retrieval of desired results.

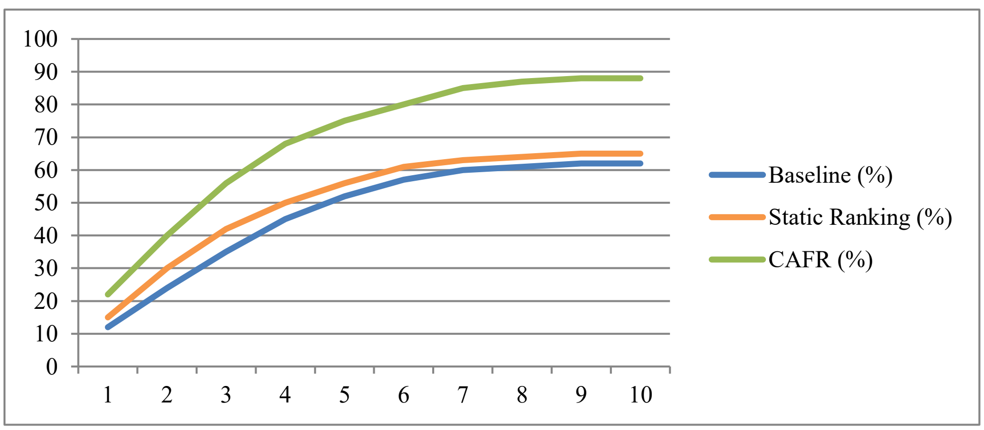

Fig. 5 Success Rate of Complex Query Resolution

Fig. 5 shows the Success rate of complex query resolution across the three search interface configurations. The CAFR model achieves an 88% success rate in resolving complex queries, significantly outperforming the Baseline (62%) and Static Ranking (65%) models. This demonstrates the CAFR model's ability to prioritize the most relevant facets for complex queries, improving overall query resolution efficiency.

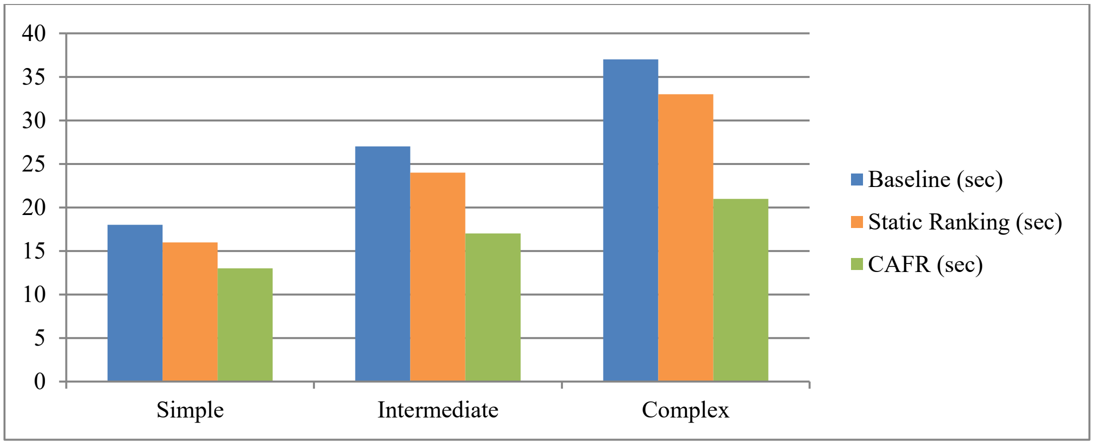

Figure 6: Average Time-to-Result per Query Type

Fig. 6 illustrates the Average time-to-result for three types of queries (Simple, Intermediate, and Complex) across the three search interface configurations. The CAFR model outperforms both the Baseline and Static Ranking models in terms of time efficiency, with the lowest average times: 13 seconds for Simple, 17 seconds for Intermediate, and 21 seconds for Complex queries. This demonstrates that the CAFR model saves time-to-result, especially in more complex queries.

V. Discussion

The results of this study emphasise the necessity of simplification of faceted search interfaces, particularly in cases where multifunctional or complex search tasks are performed. The majority of the faceted systems work on the pre-defined or frequency-based ordering of the facets, which fails to reflect the intent complexity and intent richness of users. The effectiveness of improvements in precision, interaction efficiency, and satisfaction with the Context-Aware Facet Ranking (CAFR) model shows that information retrieval systems can be significantly improved with user interfaces that consider and adapt to change. From a system design point of view, the CAFR model advocates for an increased focus on customizable and flexible default faceting filters instead of uniform faceting filters. This is particularly important in systems with high information order and delicate user goals like e-commerce, digital libraries, academic databases, and enterprise search systems. Through the active bottom-up alteration of underlying reasoning systems that assume user intent is captured by preset navigation paths, retrieval systems reduce the information overload and the time it takes to provide relevant results. Such outcomes foster a shift within information retrieval systems towards intelligent interaction designs that align with actual user behavior and context.

While the CAFR model demonstrates strong results on academic and e-commerce datasets, its scalability in handling vast datasets in real-world systems such as large-scale e-commerce platforms or extensive digital libraries remains an open challenge. In e-commerce systems with millions of products, or in digital libraries with thousands of documents, the model may face performance bottlenecks due to the complexity of real-time facet ranking and user interaction processing. Future work should focus on optimizing the CAFR model to efficiently handle large-scale datasets. Also, one can consider distributing computing, parallel processing, or compressing the model to improve the computational efficiency of the model and to make it applicable in systems with enormous amounts of data.

The model of CAFR has demonstrated significant benefits, though there are areas that need further research to develop and expand these results. An opportunity that can be exploited is automatic facet ranking by way of real-time user input, as implicit click, gaze eye tracking, or even eye tracking data, to personalize feedback. This would enable one to learn in a session and modify suggestions in real time because of micro-interaction. The model can also be projected to indicate the cross-domain validity by pushing the model to a slight stretch beyond the data upon which the model was tested. To experiment with the generalizations of the model, it can be helpful to explore the multimedia repositories, or even legal document archives, or medical information systems. Further, the study can be expanded to other studies to investigate the applicability of CAFR, along with NLP, to query intent comprehension, particularly on conversational and voice-activated systems. It can even overdo personalized search results by adjusting the algorithm to take into account user profiles, as well as long-term preferences. In addition, a study that focuses on how users become more responsive and use faceted interfaces over time will significantly contribute to the body of knowledge on the relevance and usefulness of the optimized faceted search system in the long run.

The implications of this research are quite dramatic when applied to other fields, particularly in systems that have massive amounts of content, which involve vast searching. Online shopping can use faceted search as a way of optimizing search to allow customers to access products more quickly, and this can be used to increase sales and customer satisfaction. As long as contextually relevant filters are highlighted, such as past activity, selections, or browsing activities, and the chances of visitors leaving the site are minimized. Optimized interfaces in academic and enterprise search facilities may be a more convenient way to access documents, research material, or relevant case studies, and information on a more useful basis. An example of this would be an internal database of a law firm that could implement CAFR-like models of accenting the case laws and statutes in question as a result of contextual signals in legal questions. On such public information portals as government data repositories and digital libraries, faceted search can be applied to make the portals as helpful as possible to non-experts. Such system designs that keep the context of the user in consideration ease handling valuable complex datasets and information.

Fast directions. The future research can include the incorporation of implicit user response systems, i.e., eye tracking or gaze data, to dynamically rearrange facet ranking in real-time as user interactions occur. This technology would also be a supplementary contribution towards what such users already have in mind, and tailored and attentive features would be provided even further. Natural language processing (NLP) algorithms can be implemented, which would be very helpful in helping the model to figure out the intention of the user and predict user intention, particularly in a conversational search environment. NLP will enable the CAFR model to handle larger, multi-turn queries and will also enhance its versatility in various tasks across multiple systems, including voice search and chatbot dialogues. In addition, the study of adding machine learning to support a continuous adjustment based on the feedback of the users can enable the CAFR model to be optimized and adjusted over time, and the search process based on the user will be more individualized.

VI. Conclusion

The results presented in this paper demonstrate that the effectiveness of querying in information retrieval systems can be enhanced by optimizing context-aware models, such as CAFR, with respect to navigation in faceted search interfaces. The accuracy, the use of system interactions, the success rates, and the satisfaction rates were therefore improved, particularly in complex search tasks. All these enormous developments were justified mainly by the dynamic prioritization of facet values based on the user's scene and query intent, which facilitated easier and more natural navigation through a rich information system. Designers can also expand faceted search systems further by adding real-time interaction data, facilitating adaptive learning, and further analyzing conversation or natural language input. It is also important to mention that a need to ensure scalability and cross-domain applicability in order to address the needs of different users on different platforms. It is necessary to maintain the accessibility and relatability of the new digital interface when the volume and complexity of content are expanded. Complex and sophisticated querying is essential to provide. Computerized faceted search is not merely a matter of having choices to apply filters, but one that employs intelligence to help direct the searcher to narrow down and accomplish the objectives with the least amount of effort. The fact that these issues have been resolved is a significant step forward in inventing technologies that suit the user's needs, thereby facilitating the acquisition and search of information.

References

[1] Alsmadi, M. K., Mohammad, R. M. A., Alzaqebah, M., Jawarneh, S., AlShaikh, M., Smadi, A. A., Alghamdi, F. A., Alqurni, J. S., & Alfagham, H. (2024). Intrusion Detection Using an Improved Cuckoo Search Optimization Algorithm. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 15*(2), 73–93. https://doi.org/10.58346/JOWUA.2024.I2.006

[2] Bast, H., & Weber, I. (2006). When you're lost for words: Faceted search with autocompletion. In *SIGIR* (Vol. 6, pp. 31-35).

[3] Bast, H., Chitea, A., Suchanek, F., & Weber, I. (2007, July). Ester: efficient search on text, entities, and relations. In *Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 671-678). https://doi.org/10.1145/1277741.1277856

[4] Bates, M. J. (1989). The design of browsing and berrypicking techniques for the online search interface. *Online review*, *13*(5), 407-424. https://doi.org/10.1108/eb024320

[5] Bibhu, V., Bhanot, D., Upadhyay, S., & Raghavendra Prasad, H. D. (2025). Evaluation of Engine Performance and Emissions with Biodiesel Blends Containing Polymer Waste Additives. *Natural and Engineering Sciences, 10*(1), 340–351. https://doi.org/10.28978/nesciences.1648737

[6] Castillo, M. F., & Al-Mansouri, A. (2025). Big data integration with machine learning towards public health records and precision medicine. *Global Journal of Medical Terminology Research and Informatics*, *3*(1), 22-29.

[7] Dash, D., Rao, J., Megiddo, N., Ailamaki, A., & Lohman, G. (2008, October). Dynamic faceted search for discovery-driven analysis. In *Proceedings of the 17th ACM conference on Information and knowledge management* (pp. 3-12). https://doi.org/10.1145/1458082.1458087

[8] Donkor, K., & Zhao, Z. (2024). The Impact of Digital Transformation on Business Models: A Study of Industry Disruption. *Global Perspectives in Management*, *2*(3), 1-12.

[9] Hearst, M. A. (2006). Clustering versus faceted categories for information exploration. *Communications of the ACM*, *49*(4), 59-61.

[10] Jaiswal, H., & Pradhan, S. (2023). The Economic Significance of Ecosystem Services in Urban Areas for Developing Nations. *Aquatic Ecosystems and Environmental Frontiers*, *1*(1), 1-5. https://doi.org/10.70102/AEEF/V1I1/1

[11] Koren, J., Zhang, Y., & Liu, X. (2008, April). Personalized interactive faceted search. In *Proceedings of the 17th international conference on World Wide Web* (pp. 477-486). https://doi.org/10.1145/1367497.1367562

[12] Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. *Computer*, *42*(8), 30-37.

[13] Kules, B., & Capra, R. (2009, June). Designing exploratory search tasks for user studies of information seeking support systems. In *Proceedings of the 9th ACM/IEEE-CS joint conference on Digital libraries* (pp. 419-420). https://doi.org/10.1145/1555400.1555492

[14] Lee, B., Smith, G., Robertson, G. G., Czerwinski, M., & Tan, D. S. (2009, April). FacetLens: exposing trends and relationships to support sensemaking within faceted datasets. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1293-1302). https://doi.org/10.1145/1518701.1518896

[15] Macalino, S. J. Y., Basith, S., Clavio, N. A. B., Chang, H., Kang, S., & Choi, S. (2018). Evolution of in silico strategies for protein-protein interaction drug discovery. *Molecules*, *23*(8), 1963. https://doi.org/10.3390/molecules23081963

[16] Mahdi, M. N., Ahmad, A. R., Natiq, H., Subhi, M. A., & Qassim, Q. S. (2021). Comprehensive review and future research directions on dynamic faceted search. *Applied Sciences*, *11*(17), 8113. https://doi.org/10.3390/app11178113

[17] Marchionini, G. (2006). Exploratory search: from finding to understanding. *Communications of the ACM*, *49*(4), 41-46. https://doi.org/10.1145/1121949.1121979

[18] Moravej, Z., Behravesh, V., & Bagheri, S. (2015). Optimal PMU Placement for Power System Using Binary Cuckoo Search Algorithm. *International Academic Journal of Innovative Research, 2*(2), 48–59.

[19] Osterhoff, J., Waitelonis, J., & Sack, H. (2012). Widen the Peepholes! Entity-based Auto-Suggestion as a rich and yet immediate Starting Point for Exploratory Search. In *INFORMATIK 2012* (pp. 1039-1046). Gesellschaft für Informatik eV.

[20] Rahim, R. (2024). Optimizing reconfigurable architectures for enhanced performance in computing. *SCCTS Transactions on Reconfigurable Computing*, *1*(1), 11-15.

[21] Ramona, P., & Danica, G. (2023). Analysis, Cost Estimation, and Optimization of Reinforced Concrete Slab Strengthening by Steel and CFRP Strips. *Archives for Technical Sciences, 2*(29), 35–48. https://doi.org/10.59456/afts.2023.1529.035P

[22] Revathi, R. (2024). Malgudi A Fictional World: A Critical Study of R.K. Narayan's Malgudi Days. *International Academic Journal of Social Sciences, 11(*1), 48–50.
https://doi.org/10.9756/IAJSS/V11I1/IAJSS1107

[23] Salman Mohajer, F. (2016). Reviewing the overlap of results among Google, Yahoo, and Bing search engines. *International Academic Journal of Science and Engineering*, *3*(1), 60-66.

[24] Sravana, J., Indrani, K. S., Saranya, M., Kiran, P. S., Reshma, C., & Vijay, V. (2022). Realısatıon of Performance Optımısed 32-Bıt Vedıc Multıplıer. *Journal of VLSI circuits and systems*, *4*(2), 14-21. https://doi.org/10.31838/jvcs/04.02.03

[25] Stoica, E., Hearst, M. A., & Richardson, M. (2007, April). Automating creation of hierarchical faceted metadata structures. In *Human language technologies 2007: The conference of the North American chapter of the association for computational linguistics; proceedings of the main conference* (pp. 244-251).

[26] Teevan, J., Dumais, S. T., & Horvitz, E. (2005, August). Personalizing search via automated analysis of interests and activities. In *Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 449-456). https://doi.org/10.1145/1076034.1076111

[27] Tirkey, S., Mishra, D., & Mahalik, D. K. (2020). A Study on 'Why Outsourcing in Health Care' by Friedman: Two-way Analysis of Variance Method. *International Academic Journal of Organizational Behavior and Human Resource Management, 7*(1), 01–08.
https://doi.org/10.9756/IAJOBHRM/V7I1/IAJOBHRM0701

[28] Veerappan, S. (2023). Designing voltage-controlled oscillators for optimal frequency synthesis. *National Journal of RF Engineering and Wireless Communication*, *1*(1), 49-56.

[29] White, R. W., Ruthven, I., & Jose, J. M. (2005, August). A study of factors affecting the utility of implicit relevance feedback. In *Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 35-42). https://doi.org/10.1145/1076034.1076044

[30] Whitmore, J., & Fontaine, I. (2024). Techniques for Creating, Extracting, Separating, and Purifying Food and Feed Using Microalgae. *Engineering Perspectives in Filtration and Separation*, 28-33.

[31] Yee, K. P., Swearingen, K., Li, K., & Hearst, M. (2003, April). Faceted metadata for image search and browsing. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 401-408). https://doi.org/10.1145/642611.642681