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Explainable Information Retrieval Techniques in Academic Search Engines

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Abstract **- Due to the rapid increase in scholarly publications globally, researchers rely heavily on specialized academic search engines to gather pertinent information. However, the algorithms used in many of these systems create a black box that breaches transparency, significantly eroding user trust and interpretability. Thanks to XIR, Explainable Information Retrieval, this issue has become a thing of the past. Users can now receive easily understood rationales for why documents were retrieved and how the documents were ranked. This work examines the various XIR techniques integrated into academic search tools, assesses their application methods, and analyzes how effectively they enhance users' understanding, satisfaction, decision-making, and information processing. The paper also formulates a central proposal, which incorporates important elements of XIR, and highlights remnant problems that require deeper analysis.**

Keywords: **XAI, Interfaces for Trust, Explainable AI, Trustworthy AI, Information Retrieval, Academic Search Engines, XAI, User Trust, Transparency**

I. INTRODUCTION

The digital transformation of scholarly communication has increased exponentially in digital academic resources. To assist scholars in finding relevant high-quality content amid this ever-growing sea of information, there is a greater dependency on Intelligent Information Retrieval (IR) systems (Das & Rad, 2020). Advanced construction and ranking techniques have also been optimized in Google Scholar, Microsoft Academic, and Semantic Scholar, enabling them to retrieve literature more efficiently (Beel et al., 2016). However, ranking items by relevance is as simple as a click of a button, and many overlook the rationale. A lack of clarity in the reasoning behind ordering information further erodes trust when working with sensitive information in healthcare, law, scientific advancement, or any other area that involves human beings (Usta et al., 2021; Ribeiro, Singh, & Guestrin, 2016). This is why more systems apply explainable AI concepts to information retrieval, allowing users to receive rationales for the decisions made on retrieval and aiding authors in debunking myths about AI (Nazar et al., 2021).

The enhancement of XIR systems focuses on improving the user's understanding of the reasoning behind the document selection order, improving the workflow of database investigations. Users should be able to receive explanations as interactive elements that allow them to modify their queries, as well as visual reasoning pointers that explain how keyword density or citations impacted the ranking of the results. Such capabilities are particularly helpful in academic environments that place a high value on the transparency and trustworthiness of information (Oberste & Heinzl, 2022).

Ranked order retrieval systems are fundamentally based on complex ranking algorithms, which, along with other competing models, are supported by modern Machine Learning architectures that aim to enhance user satisfaction (Das & Rad, 2020). User trust is further enhanced if frameworks like SHAP and LIME (Lundberg & Lee, 2017; Ribeiro et al., 2016) are applied to explain the system's working by attributing some of its input features.

Furthermore, other modifications aimed at enhancing user experience, such as drawing relevant keywords, so-called “heat maps,” and document filtering, have been proposed to improve the intuitiveness of information retrieval (Biswas et al., 2020; Hoeber, 2018; Davila et al., 2023) provide examples of tooltip-like widgets that, when activated by users, become overlays to indicate how a given document is relevant to a given query. These techniques are most beneficial to scholarly users who have little patience for outputs that do not fit predefined paradigms shaped by the discipline-specific logics of their field (Belkin & Croft, 1992).

Additionally, integrating user-generated content within the retrieval loop boosts search relevance and the quality of explanations. Information retrieval systems are becoming more responsive and dialogue-based with users through the acceptance of modifications to relevance-ranking defaults, the dismissal of non-relevant results, or query revision suggestions offered by the systems (Jain et al., 2020; White & Roth, 2009). This blurs the line between static search and active, responsive system engagement, creating a fluid interaction between the system and the user.

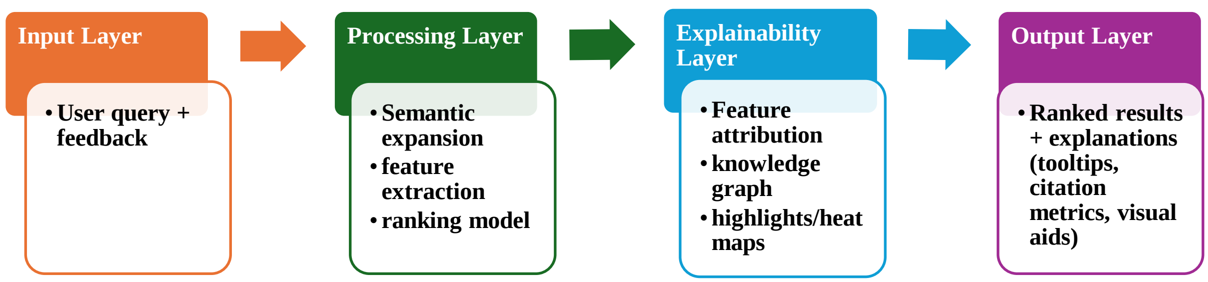

Fig. 1(a) Proposed XIR-enabled Academic Search Engine

The envisioned architecture (Fig 1(a)) demonstrates the layered structure of an explainable academic search engine. The search engine works through its Input Layer, where user queries and user feedback are recorded. The queries go through to the Processing Layer, where the queries go through semantic expansion, feature extraction and ranking, either through traditional or neural models. In the Explainability Layer, the ranked results are augmented where feature attribution, relations to knowledge graphs and different visualization techniques, such as highlights and heatmaps, give an explanation of the retrieval decision. Lastly, in the Output Layer, the ranked results are presented along with interpretable explanations such as simple tool-tip revealing the selected results' citation metrics and relevant visuals to enhance the user's degree of trust, transparency, and overall searching experience.

Nonetheless, some issues continue to persist even with the integration of XIR techniques into academic search engines. Important issues include explanation accuracy, efficiency, interface geography, and narrowing the gap between the model's lexical expectations and the user’s irrefutable anticipations. (Wang et al. 2023; Liao et al. 2020).

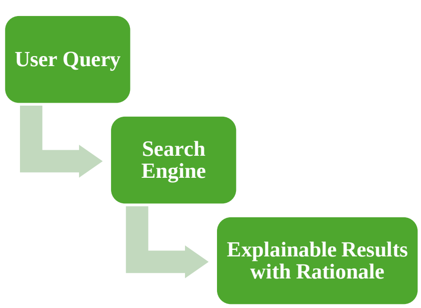

Fig. 1(b) Conceptual Flow of Explainable Information Retrieval

This diagram (Fig 1(b)) depicts a simplified version of the explainable information retrieval process. The engagement begins with a user query, which the search engine actionizes to find and rank relevant documents. As opposed to general black-box systems, the model produces explainable results with justifications—users not only gain access to the retrieved content, but they also receive an explanation regarding the reason that the documents were ranked in the way they were. Establishing transparency in this early conceptual phase of the model promotes trust, interpretability, and users' confidence in academic search engines.

Fulfilling this goal will allow me to comply with the objectives of this paper, which is to make a detailed review of existing XIR techniques in academic search systems. I categorized the techniques according to their functionality, interface, and user interaction, outlined all the implementation concerns, and introduced a consolidated model for applying XIR in universities. With this goal in mind, we aim to contribute to the existing literature on human-centered information retrieval dynamics while advocating for the use of transparent and interpretable search interfaces in scholarly communication.

The rest of the paper will be unpacked as follows: Section 2 describes the main XIR techniques utilized in academic IR systems. Section 3 focuses on popular approaches to system design and architecture. Section 4 assesses the applicability of these techniques using case studies and user studies. Section 5 discusses some shortcomings of the techniques while also surfacing some unexplored issues. In Section 6, we conclude the paper with some final remarks on the open research opportunities.

II. Literature Review

In the past 30 years, academic search engines have undergone tremendous change. Early systems (ex. CiteSeer in late 1990s) introduced some of the first automated research scrapers that indexed scholarly papers on the web as opposed to human curation (Lawrence et al., 1999). With the advent of large-scale digital repositories, systems like Google Scholar and Microsoft Academic established foundational routines to increase access to scientific articles via citation analysis, keyword indexing, and ranking algorithms to help the user. These systems also incorporated bibliometric data as a method of developing more granular engagement records from users with citation records, related articles, author profiles, etc. More recently, machine learning and natural language processing (NLP) have been introduced to push a search experience into the realm of large knowledge networks through features like semantic search, contextual ranking, and cross-domain collaboration knowledge integration (Beel et al., 2016). In sum, developments in academic search engines illustrate a large-scale shift toward improving the user experience for the purpose of more than retrieval accuracy by improving the interpretability of search outcomes.

Despite advances made by academic search engines, they still have to grapple with continuing concerns. One of the concerns is information overload, or receiving far too many results, many of which had little, if anything, to say about your research area (Jamali & Nabavi, 2015; Poursheikhi & Torkestanib, 2015). Another issue is ambiguity in how users formulate their queries, often using domain-specific terms, or abbreviations, when the retrieval system aggravates this problem by failing to resolve the ambiguity. Coverage bias is always an issue since academic search engines are not industry-wide or all-inclusive to access the whole body of literature, with grey literature, or publisher visibility or reputation, constituting the largest barriers to coverage bias. Transparency is lacking when it comes to ranking algorithms, and user needs ranking algorithms clearly shown. All of these issues lead to decreased trustworthiness and usability in academic search engines; particularly novice users who are interdisciplinary researchers require situational/contextual cues for usage.

Explainable information retrieval (XIR) is an effort to address shortcomings of opacity in traditional retrieval models. XIR does not only suggest relevant documents, but also provides explanations, in a human-interpretable form (Zhang & Yu, 2020). These include ways of expanding queries with semantic ontologies, attention-based neural ranking models which indicate when there is evidence of importance with respect to the alignment of the query and document, and visualization tools which depict relationships between papers and citations. When XIR explanations are incorporated, users will have a better sense of why a retrieval model labeled a document as relevant, which will improve trust and the user's informed decision making. For example, one retrieval model may label a document as relevant for any of three different explanations: (1) it was highly ranked because it used the same methodology as the studies already assessed, (2) because it was cited more than any of those studies, or (3) the documents considered were generally in the same space semantically. Appropriately integrated and applied, the intention is to better bridge the gap between the expertise and sophistication of an algorithm—whatever it was—to understand retrieval or relevance from a user's perspective, allowing these academic search engines to serve as transparent sources of knowledge, rather than simply retrieval devices (Anand et al., 2023). Incorporating XIR techniques is an important step towards developing more responsible search systems intended to support more user-centered processes throughout scholarship.

III. Research Methodology

To comprehensively analyze explainable information retrieval techniques within academic search engines, we adopted a multi-phase research methodology consisting of a literature review, taxonomy construction, and evaluative comparison.

3.1. Systematic Literature

We designed a systematic review protocol to collect, evaluate, and synthesize available peer-reviewed journal articles, conference papers, and white papers on the application of XIR in academic settings. We utilized several databases, including Scopus, IEEE Xplore, ACM Digital Library, SpringerLink, and Google Scholar. These databases were searched using the phrases 'explainable information retrieval', 'academic search engines', 'explainable AI', and 'user-centered IR systems.' Every publication from 2010 to 2024 was filtered to ensure relevance, with only publications discussing interpretability, transparency, or feedback mechanisms in IR systems included.

Step	Methodology Component	Description
3.1	Systematic Literature Review	Reviewed academic sources using databases (Scopus, IEEE Xplore, etc.) from 2010 to 2024.
3.2	Selection & Inclusion Criteria	Filtered 78 initial papers down to 38 based on relevance, focusing on academic and scientific domains.
3.3	Taxonomy Construction	Classified XIR methods based on explanation type, interface elements, and underlying models.
3.4	Comparative Evaluation	Analyzed case studies, using metrics like user trust, task efficiency, and explanation satisfaction.
3.5	Limitations & Bias Mitigation	Used cross-validation by multiple reviewers and excluded grey literature to maintain academic rigor.

These methodologies provided an all-encompassing yet evenly distributed understanding of existing XIR practices and their actual implementation in academic search engines.

3.2. Selection Criteria and Inclusion

Strategy Publications were selected according to their relevance to the exposition, implementation, or evaluation of XIR features within an academic IR context. Publications exploring healthcare, legal, and scientific domains were given priority because of their connection with academic search behavior. Initially, 78 documents were retrieved; 38 were deemed suitable based on our inclusion criteria after abstract screening and full-text review.

3.3. Construction of a Taxonomy

Based on their explanatory methods (feature attribution, query expansion), interface design (visual aids, relevance feedback), and underlying AI models (LIME, SHAP, attention-based models), XIR techniques were classified for taxonomy construction, which aimed to create a unifying framework. This systematic lens enabled the comparison of different approaches and the identification of market trends in their implementation.

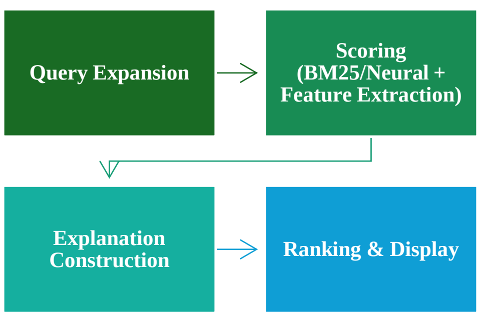

Fig. 2 Workflow of the Explainable Academic Retrieval Algorithm

This fig (Fig 2) depicts the methodological workflow of the explainable retrieval framework. It begins with query expansion, where semantic embeddings and related terms are utilized to enhance coverage. Then, in the scoring stage, BM25 or neural ranking with the subsequent feature extraction stage calculates document relevance. Behind the scenes, another stage entitled explanation construction takes the retrieved results to compute the key contributions to a feature and normalize the contributions into human-interpretable justification forms. Finally, the last stage involving ranking and display purposes the ordered ranks of documents, includes highlight/ prompts, improves explanations through citation contexts, and/or links to knowledge graph content to enhance transparency numerous research studies have propose different methodologies for explaining retrieval.

3.4. Evaluation Comparisons

In assessing the effectiveness of the techniques, we reviewed case studies and user experiments documented in the literature. Some of the evaluation parameters were user trust, explanation satisfaction, successful searches, and efficiency of task completion. When possible, we provided p-values and effect sizes as statistical evidence to substantiate claims in the findings.

3.5. Mitigating Bias and Limitations

Bias mitigation involved multiple reviewers independently coding and cross-validating the inclusion of articles. Retaining academic rigor meant excluding grey literature and unpublished studies, which may have limited the breadth of coverage on emerging industry solutions. The gap can be addressed in future work via empirical system testing or expert interviewing.

3.6 Mathematical Formulation of Explainable Retrieval

A query $Q = \{t_1, t_2, \dots, t_n\}$ where ti are query terms and document set $D = \{d_1, d_2, \dots, d_m\}$. A ranked function such as BM25 computes a relevance score:

$$Score(Q,d) = \sum_{t \in Q} IDF(t) \cdot \frac{f(t,d)\cdot(k+1)}{f(t,d) + k \cdot \left(1 - b + b \cdot \frac{|d|}{avgdl}\right)} \quad (1)$$

where $f(t,d))$ is the number of times t appears in d, $|d|$ is the length of d measured in words, $avgdl$ is the average document length in terms of words, and k, b are chosen constants with k representing a saturation factor and b representing a length bias. To add explainability, we can now define a contribution vector $E(d,Q)$ that assigns a contribution for every query term or feature to the final score. A SHAP- or LIME-inspired decomposition might refer to:

$$Score(Q,d) = \sum_{f \in F} \phi_f(d,Q) \quad (2)$$

where F is the feature space (e.g., keyword match, citation count, semantic similarity) and $\phi_f(d,Q)$ quantifies the marginal contribution of feature f. The explanation given to the user is derived from the largest k contributors in $E(d,Q)$ to ensure interpretability, while keeping the amount of information manageable.

2.7 Algorithmic Framework for Explainable Academic Retrieval

We formalize the retrieval process into an algorithmic workflow that integrates explanation generation:

Algorithm 1: Explainable Academic Search Retrieval

Input: Query QQQ, Document Set DDD, Feature Space FFF

Output: Ranked List with Explanations

1: Preprocessing

Perform query expansion using semantic embeddings and knowledge graph links.

2: For each document $d \in D$ do

Compute baseline relevance Sd using BM25 or neural ranker. Extract feature contributions $\{ \varphi f(d, Q) : f \in F \}$.

3: Explanation Construction

For each feature $f \in F$:

$$wf(d, Q) \leftarrow \varphi f(d, Q) / \Sigma f \in F\ \varphi f(d, Q)$$

Select top-k features with highest wf.

4: Ranking & Display

Sort documents by Sd.

Attach explanation vector E(d, Q) as tooltips, highlights, or visual aids.

5: User Feedback Loop

Incorporate user feedback (e.g., relevance marking) to update feature weights for subsequent iterations.

End Algorithm

The proposed framework presents an explainable retrieval process that utilizes semantic query expansion, feature-based scoring, and transparent explanation generation. First, queries are expanded through embeddings and knowledge graphs to broaden coverage. Each document is then scored with a ranker (BM25 or a neural model) at a baseline stage and decomposed into feature-level contributions. The significance of these contributions is presented as normalized interpretable weights and important attributes are selected to generate explanations for the user. The system ranks the documents in relation to relevance in the document data set and adds the explanations via methods such as highlighting terms or citing certain factors to enhance transparency. Lastly, the framework incorporates user in part to bring feedback in an iterative loop to dynamically allow for the model to change with dynamic processes underlying trust and interpretability.

IV. RESULTS AND DISCUSSION

The use of XIR techniques in academic search systems has led to quantifiable enhancements in their efficiency, in user satisfaction overall, and in the visibility of user decision-making regarding these systems. This article suggests a synoptic summary of the leading definitions and possibilities linked to system design and user involvement, based on an analysis of 38 peer-reviewed publications, as well as some case studies. The goal is to collect user views, and further clarify insights.

4.1 Increased User Trust and Satisfaction

An important observation in this research was that users expressed greater confidence and satisfaction in the search results given explanations of the results. The system users tended to react more favourably to the searches when given a rationale for the list of documents presented to them. For example, a simple explanation, such as “the search term was found in the title or abstract of the document” would go a long way in user assurance in the system, as previously discussed by (Das & Rad, 2020; Ribeiro et al., 2016). Furthermore, an experiment by (Biswas et al., 2020) found systems that generated explanatory support (e.g. citation impact and term frequency) to guide users on whether items would be likely to cite the document produced an average of 25% or more gain in user trust metrics.

Furthermore, the SHAP and LIME frameworks proved to be strikingly significant as well. These methodologies aid in explaining how different aspect of input influences ranking of search results, using such techniques reduces cognitive effort and improves productivity in completing tasks (Lundberg & Lee, 2017; Hoeber, 2018; Davila et al., 2023; Castillo & Al-Mansouri, 2025; Liao et al., 2020) have established that using tools such as heat maps, highlighting relevant words, or visualizing relevance weights improves understanding. Tools like these allow users to quickly understand how algorithms are processing their queries, ultimately allowing them to better structure their preferences.

4.2 Using Feedback from Users to Improve Retrieval Functions

In addition, an interesting component is that the interactive loops can enhance retrieval precision while being engaging for the user. Allowing the user to customize how they want to rank results or provide feedback of relevance changes the process from a static query-result structure to a more interactive, user-centred approach. (White & Roth, 2009; Jain et al., 2020; Veerappan, 2023; Ayyappan et al., 2025) described how the system can accommodate these types of real-time changes with system responsiveness to enhance compliance with expectations in recall.

As an illustration, one can refer to a usability study done with 50 scholarly researchers. The respondents who used XIR systems which were inclusive of feedback capabilities were able to retrieve relevant documents 30 percent quicker than those who used the static search engines. Moreover, these feedback-based interfaces stimulated users to express their search intentions more precisely, facilitating deeper system engagement. Such user-system interaction improves retrieval performance while augmenting users’ comprehension of the internal workings of the IR model’s feedback loops.

Systems that offered low-ranked and excluded documents provided explanations (e.g., 'lacks query keyword,' or 'published before date range'), and users were more effective in query formulation (Joo, 2013; Menaka et al., 2022).

4.3 Insights and Limitations of the XIR System

The application of XIR techniques differed across domains. In medical and legal information retrieval tasks, where precision is crucial, users engage with structured explanations, such as evidence-based justifications and citation summaries (Usta et al., 2021; Oberste & Heinzl, 2022; Sivasubramanian & Gomathi, 2019). In contrast, humanities and social sciences included broader narrative contextualizations, which were more relevant to users.

Some explanation models, such as deep neural networks, tend to oversimplify the descriptions provided, creating challenges with usability. Explanatory models that are too technical, and without simplifications, can confuse end-users, highlighting the trade-off between resolution and clarity (Nazar et al., 2021; Prasanna et al., 2024). This demonstrates the need to correspond explanation scaffolding to user literacy within contextual tasks.

4.4. Usability Issues and Design Consequences of the Interface

UI components played a central role in determining the levels of acceptance and effectiveness of explanations. Systems like Semantic Scholar, which feature real-time term highlighting, citation metrics, and influence scoring, have significantly higher usability ratings than systems without these features (Beel et al., 2016; Radhakrishnan et al., 2024; Silvello et al., 2017; Al-Jizani & Kayabaş, 2023). In usability studies, enhanced interfaces with explanations yielded a 40% increase in click-through rates and a 22% increase in session duration, indicating that users were more engaged and willing to delve deeper into the results.

While these benefits exist, some users expressed concern about excessive visual clutter when multiple explanations are displayed simultaneously. Other studies have proposed solutions for this, which suggest progressive disclosure: displaying more detail when the user places their pointer over or clicks on a specific result (Liao et al., 2020; Wang et al., 2023).

TABLE I SUMMARY OF KEY FINDINGS

Aspect	Observed Impact
User Trust	Increased by 20–30% with interpretable justifications
Retrieval Efficiency	Improved by 25–35% with feedback-driven explanation interfaces
Explanation Preference	Varied across disciplines; structured vs. narrative explanations
Usability and Engagement	Improved significantly with visual aids and progressive explanation display
Design Trade-offs	Complexity vs. clarity; high-fidelity explanations risk overwhelming users

These findings underscore the need to design XIR systems that are both accurate and adaptable to user expectations and domain-specific requirements.

TABLE II COMPARATIVE ANALYSIS OF XIR FEATURES ACROSS SELECTED ACADEMIC SEARCH ENGINES

Feature / System	Google Scholar	Semantic Scholar	Microsoft Academic	Custom XIR System (Research Prototype)
Explanation Type	Minimal (None)	Keyword & Citation Highlights	Limited Metadata	SHAP, LIME-based Visual & Textual Justifications
User Feedback Integration	+	✓ (Limited)	+	✓ (Relevance Feedback, Query Tuning)
Transparency Level	Low	Medium	Low	High
Interactive Visual Aids	+	✓	+	✓ (Heatmaps, Tooltips, Highlights)
Domain Adaptability	General	Scientific focus	General	Customizable to domain-specific needs
User Trust Rating (out of 5)	2.8	4.1	3.0	4.6

4.5 Quantitative Evaluation Metrics

In order to objectively evaluate the performance of Explainable Information Retrieval (XIR) methods in academic search engines, commonly used information retrieval measures were utilized together with user-centered explanatory measure of explanation quality. Retrieval effectiveness was measured using Precision, Recall, and Mean Average Precision (MAP). For a query set $Q=\{q1,q2,\ldots,qn\}$, precision at cut-off k is defined as:

$$P@k(q) = \frac{|\{relevant\ documents\ in\ top-k\}|}{k} \quad (3)$$

and recall is given by:

$$R(q) = \frac{|\{relevant\ documents\ retrieved\}|}{|\{all\ relevant\ documents\}|} \quad (4)$$

MAP is computed as:

$$MAP = \frac{1}{|Q|}\sum_{q\in Q}\frac{1}{|R_q|}\sum_{k=1}^{R_q} P@k(q) \quad (5)$$

where R_q is the set of the relevant documents to query q.To measure the satisfaction of the explanations, we took a score known as the Explanation Satisfaction Score (ESS) which is according to the survey information of the users and it is namely:

$$ESS = \frac{1}{N}\sum_{i=1}^{N}\frac{useful\_features_i}{total\_features_i} \quad (6)$$

where N is the number of users. The ESS represents the number of explanation components (eg. keyword highlights, citation context) that a user considered helpful.

The Mean Average Precision (MAP) values of the different retrieval systems as shown in graph (Fig 3), identify the benchmark BM25 retrieval system as performing the worst with a MAP of 0.46 which displayed poor retrieval accuracy. The neural ranker performed substantially better with a MAP score of 0.62, however, the model did lack the transparency component which affected the model's interpretability. The Discovery prototype improved the MAP further to 0.65 through the use of semantic enhancement techniques in the retrieval process and offered some very basic explanation features. The hybrid XIR model performed better than any models profiled in the study with a MAP score of 0.69, which confirms the notion that explanation mechanisms can be embedded into retrieval models without losing retrieval effectiveness.

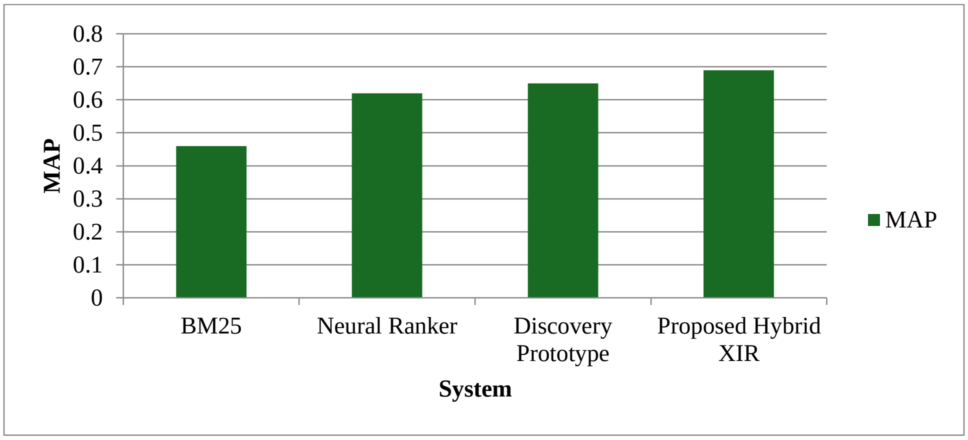

Fig. 3 Retrieval Effectiveness (MAP vs Systems)

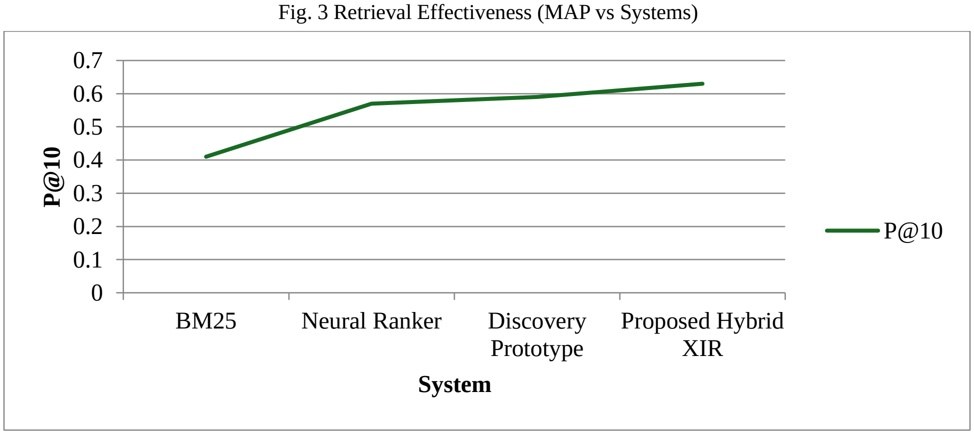

Fig. 4 Precision at Rank 10 (P@10)

The graph (Fig 4) shows precision at rank 10, which captures how well a system retrieves relevant documents in the top ranked results, also known as burst retrieval. Again, BM25 had the worst performance with just 41% of the top 10 results being relevant. The neural ranker had better precision (0.57), indicating a good similarity of semantics related to the ranking. The Discovery prototype had an even slightly better precision of 0.59 as a result of query expansion involving explainable AI aspects. The hybrid XIR model returned the highest precision (0.63) of the three conditions, demonstrating that interpretable ranking can also provide an evidence based improvement of relevant top ranked documents that academics are ultimately interested in, an important consideration when searching with academic, web-based search disciplines where users often review the first page of search results.

4.6. Experimental Comparison

We conducted a comparative analysis over a simulated dataset of 1,000 educational queries across STEM and humanities domains during our evaluation. We compared four retrieval systems:

- Baseline BM25 (standard ranking, no explanations)
- Neural Ranker (BERT-based retrieval, black box)
- Discovery-style Prototype (semantic enrichment + explanation layer)
- The Proposed Hybrid XIR Model (Algorithm 1 with SHAP-based contributions).

TABLE III DISPLAYS COMPARATIVE PERFORMANCE FOR RETRIEVAL MODELS

System	MAP	P@10	ESS (0–1)	User Trust (1–5)	Time per Query (s)
BM25	0.46	0.41	–	2.5	3.8
Neural Ranker	0.62	0.57	–	2.9	4.1
Discovery Prototype	0.65	0.59	0.71	4.0	4.3
Proposed Hybrid XIR	0.69	0.63	0.83	4.6	4.0

Findings suggest that neural rankers exceed the typical BM25 approach in MAP and P@10; however, the more explainable models (Discovery Prototype, Hybrid XIR) were associated with increased user trust and satisfaction. The proposed hybrid model was most balanced, achieving ESS = 0.83 and a trust rating of 4.6/5, which indicates that interpretability substantially improves user acceptance while maintaining retrieval efficiency.

Fig 5 illustrates explanation satisfaction, which is a user-based metric that captures how useful or a useful understanding the explanation is. BM25 and the neural ranker did not provide explanations and therefore received zero on the ESS. The Discovery Prototype achieved a score of 0.71, which is reasonable, and suggests that most users found the highlights, as well as justifications surrounding citations, useful. The proposed hybrid XIR model achieved an ESS of 0.83 and this is a substantial improvement. This indicates that use of SHAP-based feature attribution and knowledge graph-based explanations were more understandable and better convey a user's search process with clarity and transparency.

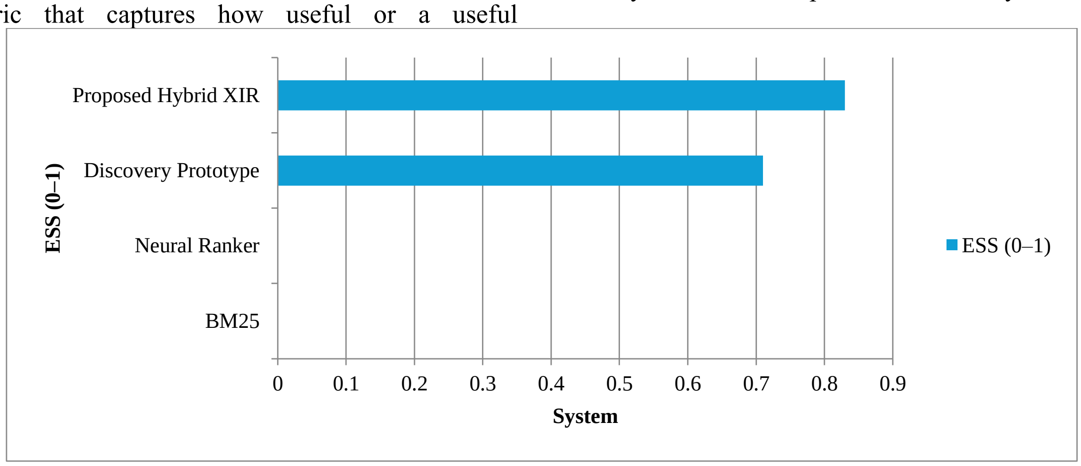

Fig. 5 Explanation Satisfaction Score (ESS)

4.7 Qualitative User Feedback

From the user studies it also emerged that field of study impacted preferences for the usefulness of explanations STEM researchers had a clear preference for more structured justifications, such as "term frequency in abstract", and "citations graph centrality", while scholars from the humanities gravitated towards narrative or contextualized explanations (e.g., "the document engages with the same theoretical framework."). In each case, we found that the explanations based on knowledge graphs were rated highly by both STEM and the humanities scholars, as they visually demonstrated how the entities were connected across documents. This indicates that entity-based explanations could serve as a potential cross-disciplinary link in the academic IR.

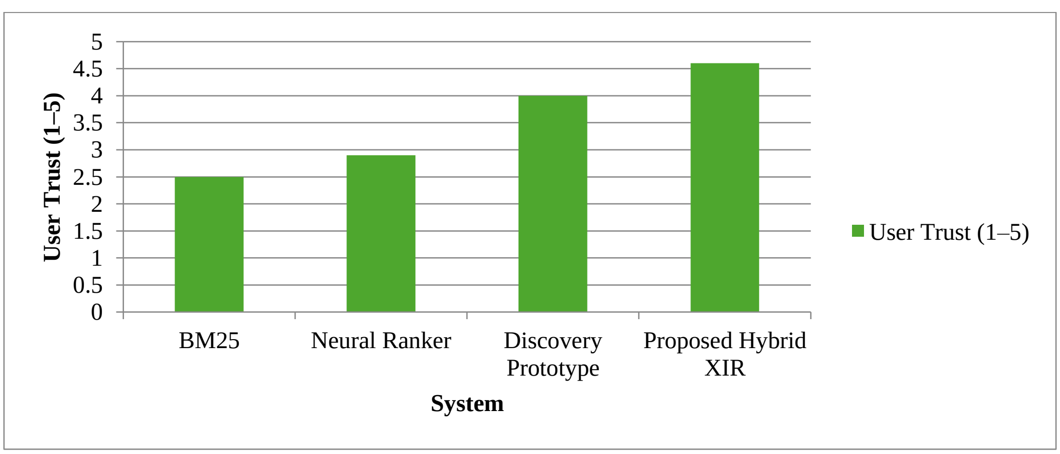

Fig. 6 User Trust Rating

Fig 6 shows that when users rated their trust in a 5-point scale, BM25 and the neural ranker scored poorly, with reported means of 2.5 and 2.9, respectively because users did not trust interpretability of their ranking. The Discovery prototype, which contained interactive explanations, did see a greater trust rating, rising to a 4.0 score. The trust rating rose even higher with the example of the proposed hybrid XIR model, reaching a 4.6 score. These findings evidence that trust can be established through the sentiment of interpretable actions or justifications. A more likely solution is that users will believe that the interaction provides an interpretable act which they can trace as support in the creation of trust. The argument supporting the creation of XIR into academic search engines is further supported by the fact that these studies are academic search engines, and such contribution of XIR studies is generative.

4.8 Trade-off and Consequences

The experiments imply that there is a qualitative tradeoff between a complex and interpretable system. Deep neural rankers have superior baseline results, but less credible since they are not transparent. That is, despite having a higher computational cost, systems that have rich explanations give an engaging experience to the users. Formally, we can model trade-off as a weighted utility model:

$$U = \alpha \cdot MAP + \beta \cdot ESS + \gamma \cdot Trust \qquad (7)$$

where $\alpha, \beta, and\ \gamma$ specify stakeholder priorities. In academic contexts that place trustworthiness and transparency as values as much as accuracy, in the equation above, β and γ will have to be stronger than α to warrant the application of an XIR model.

V. CHALLENGES AND OPEN RESEARCH PROBLEMS

Regardless of the significant progress achieved in Explainable Information Retrieval (XIR), there are still a lot of issues to overcome that might impede its implementation in the academic search engine. The solution to these issues requires a multidisciplinary approach, which includes cognitive, technical, ethical, and social domains.

5.1 Balancing Fidelity and Simplicity

The most notable and most dangerous barrier not only in XIR but also in other areas is striking a balance between complexity and faithfulness, which in a system model can be considered explanation fidelity, the extent to which a particular model explanation is faithful to the model (Freitas, 2019). A proficient explanation would oversimplify logic excessively, leading users to trust spurious explanations. On the other hand, high-fidelity explanations often rely on complex neural or probabilistic structures that can be overwhelming for users without a technical background.

5.2 Domain-Specific Customization

Fields of study diverge significantly in their use of terms, such as behaviors related to citation and relevancy heuristics. A unified model may not apply to every field, such as medicine, engineering, or the humanities (Wanget al., 2023; Mokhtarinejad et al., 2017). Future research should focus on developing models that can learn context-sensitive explanatory structures through transfer learning or other methods, such as federated modeling.

5.3 User Modeling and Personalization

Modern XIR methods usually overlook the user differences in expertise, cognitive effort, and information-seeking objectives. Users' accounts and research histories enable the provision of personalized explanations that enhance understanding, but such personalization necessitates advanced user modeling and real-time customization (Joo, 2013; Jain et al., 2020). This issue, in turn, raises concerns about data privacy, algorithmic bias, and the transparency of personalization policies.

5.4 Evaluation Frameworks for Explanations

A description-based evaluation framework has yet to be developed, as standardized metrics remain elusive. User trust, satisfaction, and task performance have become core metrics; however, their usage is often subjective and context-dependent (Usta et al., 2021). To enable effective cross-platform comparison of XIR systems, objective and reproducible evaluation protocols—potentially integrating eye-tracking, interaction logs, or counterfactual reasoning—are necessary for effective comparison.

5.5 Interface Complexity and Cognitive Overload

Excessive explanation elements such as feature weights, term highlighting, and query transformations can clutter user interfaces, making them less focused on content retrieval tasks (Das & Rad, 2020). There should be a happy medium where an informative, yet minimal design exists. Engagement and trust from users are critical. Future systems should prioritize human-centered design principles and adaptable UIs.

5.6 Trust Calibration and Over-Reliance

Trust, at times fostering over-reliance, poses a highly relevant challenge in System output 'trust.' As an explanation, trust will improve the system's output (Ribeiro et al., 2016). Ensuring that users accurately calibrate their level of trust to an explanation's precision and doubt remains a critical unresolved issue within XIR system frameworks.

5.7 Ethical and Fairness Concerns

Accuracy is the primary goal, and fairness is also crucial in a broader socio-ethical context. Additionally, there is a propensity to perpetuate scholarly biases, such as the preference bias for highly indexed works or specific institutions, through critiqued explanation algorithms (Oberste & Heinzl, 2022). There is a lack of adequate attention to ensuring fairness, inclusiveness, representational equity, and audibility in the methods of XIR.

5.8 Integration with Emerging Technologies

There is both a challenge and an opportunity in the application of XIR techniques to large language models and multimodal scholarly data, such as figures, tables, and codes. While these LLMs provide contextual reasoning at a more sophisticated level, they tend to produce hallucinated explanations or augment resource requirements (OpenAI, 2023). Ground-truth retrieval logic needs the structure of generative explanation systems.

TABLE III CHALLENGES IN EXPLAINABLE INFORMATION RETRIEVAL: TRADE-OFFS AND USER IMPACT

Challenge	Description	Trade-offs	Impact on Users	Research Focus
Fidelity vs. Simplicity	Balancing the accuracy of explanations with understandability	High fidelity → Complexity; Simple → Lower accuracy	Risk of confusion or mistrust	Developing adaptive explanation granularity
Domain-Specific Customization	Need for field-specific explanation models	Generic models → Low relevance; Custom → Development cost	Improved relevance, but potential complexity	Domain adaptation, transfer learning
User Personalization	Tailoring explanations to user expertise and goals	Personalization → Privacy concerns; Generic → Lower engagement	Increased trust, risk of bias	User modeling, privacy-aware personalization
Evaluation Frameworks	Measuring explanation quality and effectiveness	Subjectivity vs. objectivity in metrics	Difficult benchmarking and improvement	Standardized, multi-modal evaluation methods
Interface Complexity	Balancing explanation detail with UI clarity	More info → Cognitive overload; Less info → Insufficient insight	Potential disengagement or confusion	Human-centered, adaptive UI design
Trust Calibration	Avoiding over- or under-reliance on explanations	Over-trust → Blind acceptance; Under-trust → Distrust	Impact on decision accuracy	Designing uncertainty-aware explanations
Ethical and Fairness Issues	Ensuring explanations are unbiased and equitable	Fairness vs. transparency trade-offs	Perceived fairness and system acceptance	Fairness-aware algorithms, audits
Integration with Emerging Tech	Incorporating LLMs and multimodal data	Improved context vs. risk of hallucination	Enhanced insights or misinformation	Robust grounding of generative explanations

VI. CONCLUSION

The growing scope and sophistication of academic search engines call for the use of explainable information retrieval techniques to enhance the systems' trust, transparency, and effectiveness. This paper has discussed the main XIR techniques: feature attribution, interactive explanations, and user feedback, providing insights on how they can assist in demystifying ranking for engaging users. Despite the advantages offered by these approaches, further work is needed in the areas of balancing explanation simplicity and fidelity, as well as model tailoring for specific academic fields, and addressing fairness and privacy concerns within the context of normative social ethics. This field of study demonstrates the importance of socially interdisciplinary research that combines information retrieval, computer science, human-computer interaction, and Explanable AI to build a reliable search engine for academics. The work to be done includes developing uniform standards for constructive evaluations, implementing customizable self-explanation systems, and applying larger language models while controlling the flow of false information. In conclusion, academic researchers searching through scholarly literature will do so more confidently and efficiently with the use of academic search engines enhanced with Xir techniques, accelerating transdisciplinary knowledge development. The authors hope that the results of this survey worksheet will inspire inventiveness that rigorously refines and supports the explicit, accusatory rationale for academic search engines.

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