

Original Article

An Explainable Semantic Enterprise Research Network for Institutional Collaboration Recommendation

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Abstract - Universities need practical methods to integrate internal scholarly data for collaboration, discovery, and institutional decision-making. However, research information is often distributed across institutional records, ORCID profiles, and Scopus indicators, limiting the ability to identify meaningful internal collaboration opportunities. This paper presents an AI-supported explainable semantic enterprise research network for institutional collaboration recommendation. The proposed system integrates internal university records, ORCID-linked information, and Scopus-related indicators into a unified research intelligence platform. Researcher profiles are constructed from publication metadata, keywords, topics, citation indicators, publication-quality measures, and institutional attributes. The system uses OpenAI text-embedding-3-small to represent researcher profiles and applies cosine similarity to retrieve candidate collaborators. A structured AI-enrichment stage then generates shared topics, a recommendation rationale, a suggested project idea, and initial collaboration steps using pseudonymized researcher profiles. The platform was evaluated using institutional case study data, expert-based relevance assessment, additional baseline comparisons, ablation analysis, sensitivity analysis, and a preliminary user-acceptance assessment. The deployed system included 89 users, including 86 teaching and research staff, with 71% ORCID coverage and 67% Scopus coverage. The expert evaluation covered 45 recommendations for 9 target researchers and achieved a mean relevance score of 4.28, Precision@5 of 0.89, and NDCG@5 of 0.90. The proposed method performed better than keyword-overlap, BM25, and dense-embedding baselines. A preliminary System Usability Scale assessment with 15 users produced a mean score of 78.6. The results indicate that semantic profiling, institutional indicators, and explainable recommendations can support internal collaboration discovery and research monitoring.

Keywords - AI-Supported recommendation, Enterprise research network, Semantic researcher profiling, Institutional collaboration, Research analytics.

1. Introduction

Universities are now being asked to treat publications as strategic institutional resources rather than as separate academic records. The need for universities to understand how publications are produced, cited, and reused is growing due to increasing pressure on universities to manage and disseminate knowledge. As such, bibliometric research has become an increasingly valuable approach for identifying publication patterns, citation behaviour, research collaboration, and the intellectual structure of academic institutions [1]. Additionally, persistent identifier systems such as ORCID help reduce the problem of ambiguous author names and assist with linking researchers to their scholarly outputs [2]. Also, citation database systems and associated programmatic tools allow the retrieval of publication metadata, citation indicators, and author-level information from sources such as Scopus in a structured and reproducible format [3]. These developments create new opportunities for universities to build integrated research

intelligence environments that connect researcher profiles, publication records, bibliometric indicators, and collaboration-support services within one institutional platform.

Despite the wealth of scholarly data available at this time, there is a practical gap in terms of how many universities use collected research data as an effective means for internal research discovery. Faculty members are often not fully aware of colleagues who may be conducting semantically related or complementary research within their own departments, especially in multidisciplinary departments or larger institutions. As well, research administrators often require a consolidated view of researcher activity, the quality of publications produced by researchers, profile completeness, and potential collaboration opportunities across different departments and faculties. Several types of scholarly recommender systems have been developed to assist researchers with finding related papers, collaborators,



venues, datasets, and other academic resources [4]. There has also been considerable study into citation recommendation models, which can aid researchers in identifying relevant literature and increasing the completeness of scholarly writing [5]. Similar to citation recommendation models, scientific paper recommender systems have sought to decrease the amount of effort involved in searching for related work by moving beyond traditional keyword-based retrieval methods [6].

A major technical challenge for institutional research recommendations is developing ways to model researchers' interests, as well as their publications, so that they can provide recommendations that are both accurate and relevant. User-interest-based similarity measures have improved performance in recommender systems by capturing more relevant relationships between users and items [7], while recent studies on recommender systems have demonstrated that using multiple feature types and/or models can improve the quality of recommendations in real-world settings [8]. Association-rule-based recommendations have also supported requirements engineering through the identification of valuable patterns from past requirements and improvement in the completeness of recommendations [9]. All these studies suggest that institutional research recommendations can benefit from hybrid approaches that include profile data, publication content, similarity measures, and contextual institutional data.

However, although high-accuracy recommendations are important in an academic context, researchers and decision-makers need to know why a particular collaborative opportunity is appropriate, what commonalities exist among the recommended researchers' research interests, and how the recommendation can become a viable research direction. Knowledge graph-based recommender systems emphasize the value of well-defined relationships to improve both recommendation performance and interpretability [10]. Similarly, natural language processing is needed because most scholarly profiles are expressed through textual elements, such as titles, abstracts, keywords, and areas of interest [11]. Academic collaboration recommendation frameworks have also shown that suitable collaborators can be identified by considering both research-interest similarity and collaboration-network structure [12]. More recent contextual researcher recommender systems further show the value of adaptive topic modelling and semantic analysis when recommending potential research partners across multiple disciplines in an academic environment [13].

The use of Artificial Intelligence for supporting decision-making at the institutional level in higher education is becoming increasingly common [14]. However, while there are many examples of scholarly recommender systems that recommend literature, support citation recommendation, or connect users with other members of open academic

networks, fewer systems are developed and designed to support the needs of role-based enterprise platforms operating inside a single university and supporting both researchers and research administrators. Further to this, recent developments in AI-supported recommendation processes have created an increasing demand for more explainable, interactive, and context-aware recommendation pipelines [15], and therefore create opportunities to develop practical institutional systems by combining semantic profiling of researchers, collaboration scoring, explanation-oriented outputs, and role-based dashboards in a deployed university environment.

Another important issue is that recommendation systems should be evaluated not only by the existence of ranked outputs, but also by the relevance, usefulness, and interpretability of the generated recommendations. Previous studies on recommender-system evaluation emphasized that different evaluation settings may capture different aspects of recommendation quality, including prediction accuracy, ranking quality, user tasks, and system usefulness [16]. User-centred evaluation has also been highlighted as an important direction because the practical value of a recommendation depends on how users perceive its relevance, transparency, and decision-support value [17]. Therefore, evaluating institutional collaboration recommendations should consider system deployment, expert-based relevance judgement, ranking-quality metrics, and comparison against simpler recommendation baselines.

This study aims to fill this gap by developing an explainable semantic enterprise research network for institutional collaboration recommendation. The proposed platform combines the research profile of each researcher with ORCID-linked information, Scopus-related publication indicators, and institutional metadata into a unified research intelligence environment. The recommendation process uses dense semantic profile representation, similarity-based candidate retrieval, and a structured AI-enrichment stage for explanation and project-synthesis outputs. The proposed platform differs from systems that return only lists of names or numerical rankings because it provides explanation-oriented outputs that describe why a recommendation was generated. These outputs include common topics between recommended collaborators, similarity indicators, a short rationale, an initial project idea, and first collaboration steps. The system is implemented as a role-based web platform that serves researchers, research administrators, and system administrators, making it useful for individual research discovery and institutional research-performance monitoring.

The proposed collaboration recommendation system is examined using an actual university as a case study. The evaluation uses evidence from institutional deployment, expert-based assessment of generated recommendations, ranking-quality measures, ablation and sensitivity analysis,

user-acceptance assessment, and comparison against keyword-overlap, BM25, and dense-embedding baselines. In addition to evaluating whether the framework can produce collaboration suggestions, the evaluation examines whether these suggestions are relevant, interpretable, and more useful than simpler retrieval baselines.

The main contributions of this paper are summarized as follows:

- A deployed enterprise research intelligence platform is developed to integrate internal researcher information with ORCID and Scopus-related scholarly indicators.
- An explainable semantic collaboration recommendation mechanism is proposed by combining dense researcher-profile embeddings, similarity-based candidate retrieval, and structured AI-enrichment outputs.
- Role-based dashboards are provided for researchers, research administrators, and system administrators to support research discovery, collaboration planning, profile monitoring, and institutional research analytics.
- The proposed recommendation mechanism is evaluated using a real university case study, expert-based relevance assessment, ranking-quality metrics, additional baselines, ablation and sensitivity analysis, and user-acceptance assessment.

2. Related Work

Scholarly recommender systems have been widely investigated because of the rapid growth in academic publications and because it has become difficult for researchers to manually identify all relevant studies in their fields. Most of these systems were developed mainly to help researchers find papers that are close to their interests or previous work. For example, Beel et al. reviewed the development of research-paper recommender systems and showed that many of the commonly used approaches in this area include content-based filtering, collaborative filtering, citation analysis, and hybrid methods [18].

Sugiyama and Kan also proposed a recommendation approach that depends on the recent publications of a researcher as an implicit representation of research interests, which shows that publication history is an important source for personalizing academic recommendations [19]. In addition, Haruna et al. introduced a collaborative recommendation method that uses publicly available contextual metadata and citation relations between papers, so that relevant papers can be recommended even when full-text access to all candidate papers is not available [20].

Although these studies are useful for understanding scholarly recommendations, they are still mainly concerned with recommending papers. Therefore, they do not directly address the institutional problem of discovering possible collaboration opportunities among researchers working within the same university environment.

Research collaboration recommendation can be viewed as a more focused extension of scholarly recommendation, since the aim is not only to recommend papers, but also to identify researchers who may be suitable for future collaboration. Several studies have investigated this direction using network and content information. Yang et al. proposed HNRWalker, a heterogeneous-network-based random walk model that combines institutional and co-author networks to recommend academic collaborators based on dynamic transition probabilities [21]. Chen et al. developed a content-enhanced network embedding model that integrates researcher textual information with collaboration-network structure, which shows that collaborator recommendation can be improved when semantic information and structural relationships are considered together [22].

Zhu and Yaseen further used a graph neural network-based approach with MEDLINE data, demonstrating that graph-based models can capture complex and time-related dependencies between researchers [23]. These works show the value of network topology, textual content, and machine-learning-based representation in academic collaborator recommendation. However, they remain largely focused on external datasets or open scholarly networks, while the problem addressed in this study is more institutional in nature, since it concerns a deployed university platform that supports collaboration discovery as part of broader research-management needs.

There is an additional direction that motivates this study, which is explainable recommendation. While recommender systems provide recommendations, they should also explain the reasons behind these recommendations to their users. Zhang and Chen argue that explanations are important in recommender systems because they help increase transparency, trust, persuasiveness, and acceptance [24]. This becomes especially important in a university environment, where different stakeholders, such as researchers, administrators, and research offices, may use collaboration recommendations. Therefore, the system should be able to show why a particular researcher was recommended and what evidence supports that recommendation. Institutional bibliometric reporting is also becoming increasingly important for universities because it provides structured information about publication activity, citation indicators, and research performance.

Cabezas-Clavijo and Torres-Salinas discussed institutional bibliometric reporting and highlighted how structured research indicators can support responsible research assessment [25]. Taken together, these two lines of work indicate that institutions do not only need to identify potential collaborators through a collaboration recommendation system, but also need to explain the rationale behind the recommendation and connect it with bibliometric evidence within a single university research intelligence platform.

Although previous studies have made important contributions to scholarly recommendation, collaborator discovery, explainable recommendation, and bibliometric reporting, several limitations remain. Many systems focus on recommending papers or citations rather than identifying explainable collaboration opportunities within a single institution. Other approaches rely heavily on external academic networks and do not provide role-based dashboards for researchers, research administrators, and system administrators.

In addition, existing systems often return ranked recommendations without sufficient institutional explanation, making it difficult for users to understand the rationale behind the suggested collaboration. From an evaluation perspective, recommendation quality should also be examined in terms of relevance, usefulness, ranking quality, expert or user judgement, and comparison with simpler retrieval baselines [16], [17].

Therefore, this study proposes an explainable semantic enterprise research network that integrates researcher profiles, ORCID and Scopus-related indicators, semantic similarity, AI-supported explanation, and institutional metadata to support internal collaboration recommendation and research-performance monitoring. The proposed system is further evaluated through expert-based relevance assessment, user-acceptance assessment, ablation and sensitivity analysis, and comparison against keyword-overlap, BM25, and dense-embedding baselines.

3. Proposed Methodology

The purpose of the proposed methodology is to establish an explainable semantic research network in order to provide collaboration recommendations among researchers within the university environment. The primary objective is to convert separate scholarly records into one coherent research intelligence space, thus providing a common platform for representing each researcher's profile along with publications, citation indicators, publication-quality measures, and institutional affiliations. In contrast to treating research outputs as independent records, the system examines relationships among researchers through their respective publication profiles, research topics, scholarly indicators, and institutional context.

The methodology uses two interdependent aspects to guide the formation of an Enterprise Research Network (ERN) and evaluate its performance. The first aspect refers to the construction of the basic building blocks required for the ERN. In this context, these include data unification, the construction of researcher profiles, the calculation of semantic similarity among researchers, the calculation of collaboration scores for pairs of researchers, the production of explanations for the suggested collaborations, and role-based dashboards. The second aspect refers to the evaluation

of the quality of the suggestions produced by the system through multiple methods, including relevance evaluations performed by experts, ranking-quality metrics, and comparison with a baseline method based on keyword overlap. By combining both aspects, this design ensures that the proposed system is evaluated from two distinct perspectives. First, it is evaluated as a deployed institutional platform. Second, it is evaluated as a mechanism for producing recommendations whose outputs can be analyzed in relation to their relevance, interpretability, and ranking quality.

3.1. System Overview

The proposed platform is developed as a role-based web system with three types of users: researchers, research administrators, and system administrators. Researchers use the system to view their research profiles, ORCID-linked information, Scopus-related indicators, publication summaries, and suggested collaboration opportunities. Research administrators use the system to monitor institutional research activity, publication quality, researcher engagement, department-level indicators, and overall scholarly performance. System administrators manage users, synchronize data, track the completion of researcher profiles, and ensure data quality.

The main purpose of this platform is to provide an institutional research network for the university in order to discover possible collaboration opportunities among researchers. It does so by integrating internal researcher information with external scholarly identifiers and publication-related indicators. This integrated information is then used with semantic analysis and similarity-based recommendation methods to identify relevant collaboration relationships between researchers. Figure 1 illustrates the overall architecture of the proposed enterprise research network.

Figure 1 shows an overview of the main workflow of the proposed system, starting from data sources and integration, then researcher profile creation, collaboration recommendations, and finally presentation through role-based dashboards. Overall, the system architecture consists of five main layers. The first layer includes the data sources, namely internal university records, ORCID data, and Scopus-related publication records.

The second layer performs the necessary data preparation tasks, including data collection, cleaning, normalization, and profile synchronization, in order to keep researcher information and publication records consistent and up to date. In the third layer, unified researcher profiles are generated by combining publication metadata, keywords and topics, citation and quality indicators, and institutional attributes. The fourth layer generates collaboration recommendations.

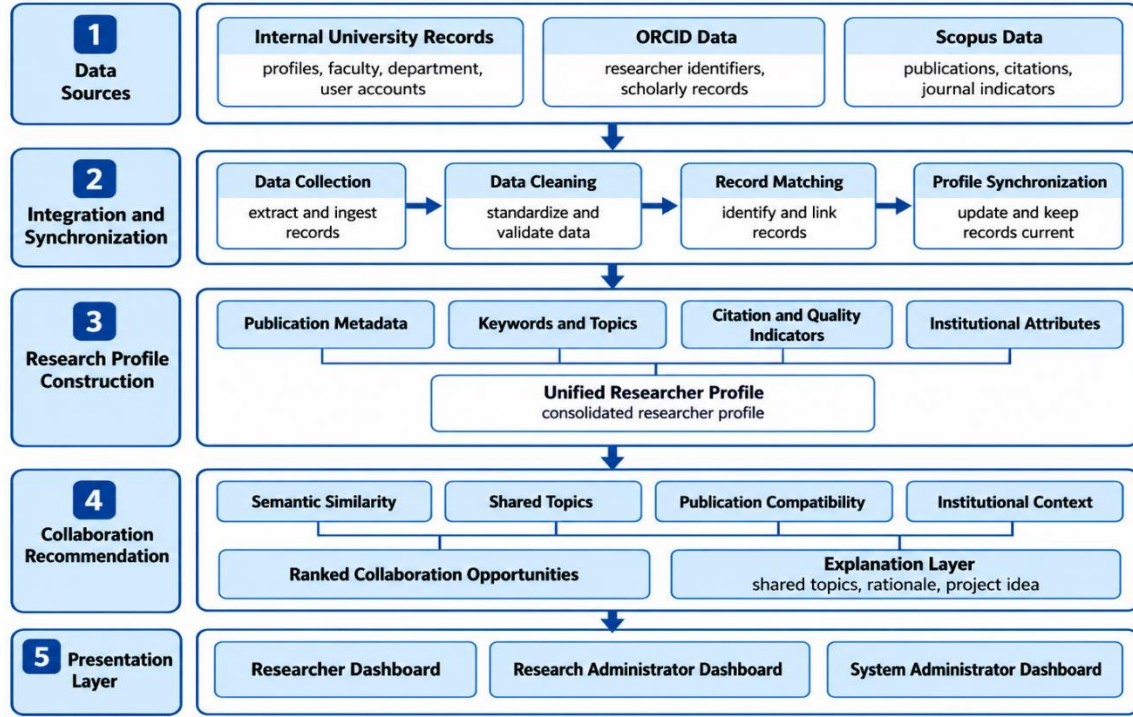


Fig. 1 Proposed architecture of the enterprise research network

Because of similar author names or unclear scholarly records, the third source is Scopus-related publication data, which provides structured information about the researchers' publications, citations, indexed outputs, journal indicators, and author-level research metrics.

The integration process begins by linking each researcher's profile with the available ORCID and Scopus identifiers. After linking, the system retrieves, stores, and updates publication-related metadata in the institutional database. Since research metadata may contain inconsistencies, the system applies normalization procedures to researcher names, publication titles, journal names, keywords, and institutional affiliations before using them in the recommendation process. These procedures reduce duplication, improve profile consistency, and support more reliable comparison among researchers.

The output of this stage is a unified researcher profile that combines institutional information, publication history, citation indicators, journal-quality indicators, and research-topic information. This unified profile provides the foundation for both individual-level research discovery and institutional-level research analytics.

3.2. Researcher Semantic Profiling

Researcher Semantic Profiling is the core representation stage in the proposed methodology. Each researcher is represented using a set of scholarly and institutional features extracted from available research records. These features

include publication titles, keywords, research areas, journal information, citation-related indicators, faculty, department, and other institutional attributes. Since scholarly expertise is mainly reflected through textual elements such as titles, keywords, and research interests, the system uses these elements to construct a semantic representation of each researcher.

For each researcher, the profile is constructed using textual, bibliometric, and institutional characteristics. The textual characteristics represent the researcher's main topics, research interests, and areas of specialization. The bibliometric characteristics describe publication activity and citation-related indicators. The institutional characteristics provide the context needed to distinguish between same-department, cross-department, and cross-faculty collaboration opportunities. The researcher's profile is represented as:

$$R_i = \{T_i, K_i, P_i, C_i, I_i\} \quad (1)$$

where R_i denotes the profile of researcher i , T_i represents the extracted research topics, K_i represents keywords, P_i represents publication-related features, C_i represents citation and quality indicators, and I_i represents institutional context such as faculty and department.

In the implemented system, textual information about a researcher is combined into a single `research_text` field. This field includes publication titles, estimated keywords, and

research-topic information derived from available publication records. The text is cleaned and normalized before vectorization. The system uses the OpenAI text-embedding-3-small model to generate a dense embedding vector for each researcher profile. Semantic similarity between two researchers is then computed using cosine similarity between their embedding vectors. The similarity score is normalized within the [0, 1] interval, where higher values indicate stronger similarity in research themes.

This representation enables the system to analyze researchers using semantic and contextual information. Similarity measures are widely used in recommender systems to identify relationships among users or items with comparable interests and profile characteristics [7]. In the proposed institutional setting, this principle is used to compare researchers according to their scholarly profiles and institutional attributes.

3.3. Collaboration Recommendation Mechanism

The collaboration recommendation mechanism identifies potential research partners by comparing the semantic profiles of researchers working in the same institution. For each target researcher, the system computes profile similarity against other researchers and retains candidate pairs whose cosine similarity is equal to or greater than 0.55. The top-10 candidate pairs are then passed to the explanation and project-synthesis stage. The scoring process considers four factors: semantic similarity, shared research topics, publication-profile compatibility, and institutional context. The collaboration score between two researchers is defined as:

$$CS(R_i, R_j) = w_1 SS(R_i, R_j) + w_2 ST(R_i, R_j) + w_3 PC(R_i, R_j) + w_4 IC(R_i, R_j) \quad (2)$$

where $CS(R_i, R_j)$ represents the collaboration score between researchers i and j , $SS(R_i, R_j)$ denotes the semantic similarity between their research profiles, $ST(R_i, R_j)$ represents the degree of shared topics or keywords, $PC(R_i, R_j)$ reflects publication-profile compatibility, and $IC(R_i, R_j)$ represents institutional context—the parameters w_1 , w_2 , w_3 , and w_4 represent the relative weights assigned to each component.

The weights were fixed as a system configuration before evaluation. Semantic similarity was assigned the highest weight because candidate retrieval depends on dense profile similarity. Shared topics were assigned the second-highest weight because direct thematic overlap remains useful for collaboration recommendations. Publication-profile compatibility was included to reflect compatibility in research outputs and publication patterns. Institutional context was assigned a smaller weight because it supports practical collaboration inside the institution, but should not

allow department or faculty proximity to dominate the ranking. Table 1 shows the recommendation components and the weights used in the implemented scoring configuration.

Table 1. Recommendation components and weights

Component	Symbol	Description	Weight
Semantic similarity	SS	Measures semantic closeness between researcher profile vectors	0.40
Shared topics	ST	Measures overlap in extracted topics and keywords	0.25
Publication-profile compatibility	PC	Measures the compatibility of publication patterns, domains, and quality indicators	0.20
Institutional context	IC	Measures institutional relationship such as department or faculty context	0.15

Semantic similarity captures the closeness between research interests using the vector-based semantic representation of researcher profiles. Shared topics identify direct thematic overlap between researchers based on extracted keywords and research topics. Publication-profile compatibility considers whether the researchers have related or complementary publication patterns, such as similar publication domains, journal areas, indexed outputs, and publication-quality levels. Institutional context helps the system distinguish whether a recommendation supports collaboration within the same department, across departments, or across faculties. All component scores are normalized to the range [0, 1] before the final collaboration score is calculated. The final score is used to rank candidate collaborators. The system does not treat the numerical score as the only output. The recommendation module also generates explanation elements that describe why a particular researcher was recommended. This is consistent with explainable recommender systems, where explanations are used to improve transparency and user trust [24]. Algorithm 1 describes the complete recommendation procedure.

3.4. Generative Explanation and Project Synthesis Engine

After candidate retrieval and scoring, the system applies a generative explanation and project-synthesis stage. This stage does not replace semantic retrieval. It is used to enrich each top-ranked candidate pair with interpretable outputs that can be reviewed by researchers and research administrators. For each candidate pair, the system sends a structured payload to the OpenAI Responses API. The payload includes pseudonymized labels for the two researchers, their cleaned research-profile text, and the embedding-similarity value.

Direct identifiers, including researcher names, email addresses, and local user IDs, are excluded from the external AI payload. The prompt refers only to Researcher A and Researcher B. The generative stage uses a fixed prompt that requires valid JSON output. The returned fields are `ai_score`, `shared_topics`, `explanation`, `proposed_project`, and `first_steps`. The prompt also constrains the explanation to the supplied profiles and requires the project idea to be realistic and useful. The structured format limits free-form output and allows the system to store the generated fields in the `collaboration_matches` table for later display and evaluation.

The fixed prompt template follows this structure: system role = university research collaboration analyst; input fields = pseudonymized Researcher A profile, pseudonymized Researcher B profile, and embedding-similarity value; output schema = `ai_score`, `shared_topics`, `explanation`, `proposed_project`, and `first_steps`.

The safeguards require JSON-only output, exclude direct identifiers, restrict the explanation to the supplied profiles, limit `shared_topics` to concise topic labels, and require the `proposed_project` and `first_steps` to remain within the provided research evidence. These constraints reduce unsupported generation by limiting the model output to the given profile content and the defined schema.

The generated rationale and project idea are treated as decision-support information, not as an administrative decision. They are displayed together with similarity values and shared topics so that users can judge whether the recommendation is suitable before any contact or collaboration is initiated.

3.5. Explainability and Role-based Dashboards

The proposed system is designed to provide explainable collaboration recommendations, rather than only presenting researchers with opaque ranked lists. For each recommended collaborator, the platform shows the collaboration score, similarity score, shared topics, related keywords, a short rationale that explains why the collaboration may be suitable, and an initial suggested project idea. These explanation elements help researchers understand the basis of the recommendation before they decide whether to contact the recommended researcher or start a possible collaboration.

Explainability is an important part of the proposed platform because the system is used within an institutional research environment. Researchers need to understand the evidence behind the suggested collaboration, and research administrators need indicators that can be interpreted and used for planning, monitoring, and strategic decisions. Therefore, the platform does not provide recommendation scores only, but also combines them with explanation-oriented outputs and institutional analytics.

The role-based dashboards are designed based on the needs of each type of user in the platform. The researcher dashboard presents the researcher's individual profile, ORCID-linked information, Scopus-related indicators, recent publications, publication-quality summaries, and suggested collaboration opportunities.

The research administrator dashboard provides institutional-level analytics, including researcher activity, ORCID and Scopus coverage, publication-quality distribution, department-level summaries, and research-performance indicators. The system administrator dashboard supports account management, data synchronization, profile-completion tracking, and system-level monitoring.

3.6. Privacy, Cold-Start, and Scalability Considerations

The platform uses institutional and scholarly metadata to support collaboration and discovery. To reduce privacy exposure in the AI-enrichment stage, direct personal identifiers are excluded from the external AI payload. Researcher names, email addresses, and local user IDs are replaced with pseudonymized labels before the generative stage. The system output is presented as a recommendation that requires human review, not as a final decision about research performance or collaboration suitability.

Cold-start cases occur when a researcher does not have enough publication metadata, ORCID-linked records, or Scopus-related information to construct a meaningful profile. In these cases, the system does not force a recommendation. The researcher's profile can be updated when additional publication records become available. This avoids generating weak matches from incomplete profiles.

The implemented pipeline also limits unnecessary recomputation. Researcher profiles are embedded once and updated when profile data changes. Candidate pairs are filtered using a minimum cosine-similarity threshold of 0.55, and only the top-10 candidates for a researcher are passed to the AI-enrichment stage. This design keeps the deployed system suitable for institutional use while limiting repeated external calls.

3.7. Evaluation Protocol

The evaluation protocol is designed to assess the proposed system from deployment, recommendation-quality, baseline-comparison, component-analysis, and user-acceptance perspectives. Evaluating a recommender system requires more than showing that the system can generate ranked outputs; it should also examine whether the generated recommendations are relevant, useful, and properly ranked for the intended task [26]. Therefore, the evaluation combines institutional deployment evidence, expert-based relevance assessment, ranking-quality metrics, baseline comparison, ablation and sensitivity analysis, and a preliminary System Usability Scale assessment.

Algorithm 1. Explainable Collaboration Recommendation Procedure

Input: Researcher profiles $R = \{R_1, R_2, \dots, R_n\}$, target researcher R_i , number of recommendations k
Output: Top- k explainable collaboration recommendations for R_i

1. Retrieve the unified profile of the target researcher R_i .
2. Construct or update the `research_text` field using publication titles, keywords, and research-topic information.
3. Generate the researcher embedding vector using `text-embedding-3-small`.
4. Construct the candidate set $C = \{R_j \in R \mid j \neq i\}$.
5. Compute cosine similarity between the embedding vector of R_i and each candidate R_j .
6. Retain candidate pairs whose cosine similarity is at least 0.55.
7. Rank retained candidates and keep the top-10 candidates for the target researcher.
8. Compute the collaboration score using semantic similarity, shared-topic evidence, publication-profile compatibility, and institutional context.
9. Send pseudonymized candidate-pair information to the generative explanation stage.
10. Generate structured outputs containing shared topics, recommendation rationale, suggested project idea, and first collaboration steps.
11. Store the ranked recommendation and explanation fields in the `collaboration_matches` table.
12. Return the top- k explainable collaboration recommendations.

First, deployment-level evidence is used to describe the operational status of the platform in a real university environment. This includes reporting the number of users, teaching and research staff, linked ORCID profiles, Scopus-covered profiles, publications, citations, publication-quality indicators, and generated collaboration opportunities. These indicators demonstrate that the platform is populated with real institutional data and can operate as a practical enterprise research network.

Second, the quality of the generated collaboration recommendations is assessed through expert-based relevance evaluation. A representative sample of collaboration recommendations is extracted from the system output. The selected recommendations are anonymized to remove personally identifiable information and are then evaluated independently by domain experts. Each expert assesses the relevance of every recommendation using a five-point relevance scale ranging from 1, indicating that the recommendation is not relevant, to 5, indicating that the recommendation is highly relevant. The assessment is based on four criteria: research-topic overlap, complementarity between researcher profiles, plausibility of future collaboration, and usefulness of the explanation provided by the system.

For ranking-based analysis, recommendations with an average expert rating of 4 or 5 are treated as relevant. The evaluation reports the mean relevance score, the percentage of relevant recommendations, Precision@5 , and NDCG@5 . Precision@5 measures the proportion of relevant recommendations among the top five results, while NDCG@5 evaluates ranking quality by giving higher importance to highly relevant recommendations that appear near the top of the ranked list. This is suitable for collaboration recommendation because users are more likely to inspect the first few suggested collaborators rather than the entire ranked list. Since the experts provide numerical ratings, inter-rater agreement is examined using intraclass correlation to evaluate the consistency of expert judgments.

Third, the proposed recommendation mechanism is compared with three baselines: keyword overlap, BM25, and dense-embedding similarity. The keyword-overlap baseline ranks candidates using direct overlap between keyword sets. BM25 ranks candidates using lexical similarity between researcher-profile texts. The dense-embedding baseline ranks candidates using cosine similarity between profile embeddings only. In contrast, the proposed method combines semantic retrieval, shared-topic evidence, publication-profile compatibility, institutional context, and structured AI-enrichment outputs. The keyword-overlap baseline score between two researchers is computed as:

$$\text{KB}(R_i, R_j) = |K_i \cap K_j| / |K_i \cup K_j| \quad (3)$$

where $\text{KB}(R_i, R_j)$ represents the keyword-based baseline score between researchers i and j , while K_i and K_j represent the keyword sets associated with the two researcher profiles.

Ranking quality is measured using normalized discounted cumulative gain at rank five. For a ranked list of five recommendations, DCG@5 is computed as:

$$\text{DCG@5} = \sum_{r=1}^5 (2^{\text{rel}_r} - 1) / \log_2(r + 1) \quad (4)$$

where rel_r represents the expert relevance score of the recommendation at rank r . NDCG@5 is then calculated as:

$$\text{NDCG@5} = \text{DCG@5} / \text{IDCG@5} \quad (5)$$

where IDCG@5 represents the ideal DCG@5 obtained by ranking the same recommendations in descending order of expert relevance, this metric is widely used in information retrieval and recommendation evaluation because it considers both relevance level and ranking position [27].

By combining deployment evidence, expert-based relevance assessment, baseline comparison, ablation analysis, sensitivity analysis, and ranking-quality metrics, the protocol provides a measurable basis for evaluating the proposed system. This makes the methodology suitable for an applied

study while allowing the recommendation outputs to be examined in relation to relevance, ranking quality, interpretability, and practical usefulness.

The proposed method uses semantic researcher profiling, collaboration scoring, explanation-oriented recommendations, role-based dashboards, and recommendation evaluation. Although the system is lightweight enough to be implemented as a web-based platform for universities, it provides a technical contribution through semantic recommendation, structured AI-enrichment, explainable outputs, and integrated research intelligence support.

4. Case Study and Evaluation

This section presents the case study and evaluation used to examine the feasibility and practical value of the proposed enterprise research network. The system was implemented in a real university environment in order to integrate researcher information, ORCID-linked data, Scopus-related indicators, publication-quality measures, and collaboration recommendations within one role-based platform.

The evaluation was designed to study the system from deployment and recommendation-quality perspectives. It reports institutional coverage, expert-based relevance assessment, baseline comparison, ablation and sensitivity analysis, user acceptance, and dashboard-based demonstration.

4.1. Case Study Setting

The case study was conducted at Al-Zaytoonah University of Jordan using the deployed web-based platform that was developed to support institutional research intelligence. The platform works with three main user roles, which are researchers, research administrators, and system administrators. Researchers can access their unified research profiles, publication indicators, ORCID-linked information, Scopus-related indicators, and the suggested collaborators generated by the system. Research administrators can monitor institutional research indicators, publication quality, department-level activity, and the coverage of scholarly identifiers. System administrators are responsible for managing users, monitoring the completeness of profiles, handling synchronization processes, and supporting data-quality monitoring across the platform.

The system integrates the internal university records with ORCID and Scopus-related publication indicators. The internal records provide the basic data about each user, including identity, faculty, department, role, and account-level information. ORCID supports researcher identification and publication linking, while Scopus-related data provide publication, citation, and publication-quality indicators. This integrated dataset allows the platform to generate individual researcher dashboards and institutional-level analytics.

4.2. Institutional Dataset and System Coverage

Table 2 presents aggregated system-wide statistics collected from the deployed research platform at the time of data collection. These statistics are reported at the system level, not at the individual researcher level, and they do not include any identifiable information about researchers. They are included only for demonstration purposes, to show that the proposed platform is operationally viable and has broad data coverage. Therefore, these statistics should not be used as an official assessment of institutional research performance or as a comparison of research performance within the institution.

The platform contains 89 user accounts, 86 of them from teaching and research personnel; one is a system administrator, and two others are research administrators. Approximately 71% of researcher accounts on the platform have been associated with their ORCID iD, and approximately 67% have been associated with Scopus-related author information. This indicates that most researcher profiles are connected to at least one external scholarly data source. A total of 31,449 citations and 1,352 ranked publications have also been collected. Also included in the data are the identification of 479 Q1, 394 Q2, 335 Q3, and 144 Q4 publications. Additionally, there are 735 identified conference papers, 46 identified book chapters, 15 other records that have no quality rank, and 45 identified collaboration opportunities.

The proposed platform is structured so that statistics are presented at an aggregated level and do not show individual researcher records. This is done to protect the researcher's privacy and avoid exposing individual researcher data. Table 2 shows how the platform allows users to see the overall research activity of the institution. Through the platform, users can bring together and review key scholarly indicators in one environment, which supports the monitoring of research activity at the institutional level. Users do not have to search for the same type of information separately from researcher profiles, ORCID records, or Scopus-related indicators. Rather, the proposed platform organizes this information and makes it easier to access, supporting the visibility of individual researchers and the monitoring of institutional research activity.

4.3. Collaboration Recommendation Output

The collaboration recommendation module identified 45 possible collaboration recommendations. These recommendations were generated by considering the researchers' similarity in academic profiles, areas of shared research focus, compatibility with respect to publication activity, and institutional context. The module presents each recommended collaboration with a collaboration score, a similarity measure, common research topics, a brief explanation, an initial project idea, and first collaboration steps. Thus, instead of presenting researchers only with a

numerical score, the platform provides recommendations that can be interpreted and reviewed.

Table 2. Aggregated institutional statistics

Indicator	Value
Total system users	89
Total teaching/research staff	86
Research administrators	2
System administrators	1
ORCID coverage	71%
Scopus coverage	67%
Total citations	31,449
Ranked publications	1,352
Q1 publications	479
Q2 publications	394
Q3 publications	335
Q4 publications	144
Conference papers	735
Book chapters	46
Unranked records	15
Identified collaboration opportunities	45

Table 3. Sample explainable collaboration recommendation output

Item	Output
Recommended pair	Researcher A × Researcher B
Collaboration score	95%
Similarity score	82%
Shared topics	Machine learning, software testing, big data, augmented software engineering, requirements engineering
Recommendation rationale	The researchers show strong overlap in research interests and complementary publication expertise in software engineering and machine-learning-related topics.
Suggested project idea	Develop an AI-supported software quality platform that combines requirements analysis, automated test generation, and machine-learning-based defect prediction.
Recommendation type	Strong collaboration opportunity

Table 3 is provided to give an example of how an explainable collaboration recommendation is generated by the platform. For privacy purposes, the researchers' names are anonymized in this paper as "Researcher A" and "Researcher B". The potential collaboration shown in the example has a high collaboration score of 95% and a high similarity score of 82%. In addition to these scores, the

common topics between the two researchers include machine learning, software testing, big data, augmented software engineering, and requirements engineering. With these scores and topic areas, the system gives a brief explanation and an initial project idea to provide the rationale for the recommendation and help the researchers consider it as a possible starting point for collaborative work.

This example illustrates how recommendations are made available to users in a usable format. In addition to providing a ranked list of possible collaborators, the system provides the primary justification for each suggestion. Since a high score alone would typically not be a sufficient reason to establish a collaborative relationship in an academic setting, it is useful for researchers to understand why a collaboration with another researcher has been recommended. This allows them to determine whether there is enough common ground to warrant further discussion or to develop the proposed collaboration into a joint research proposal.

4.4. Expert-based Recommendation Evaluation

In order to assess the quality of the recommendations produced by the system, an expert-based relevance assessment was conducted. A total of forty-five (45) collaboration recommendations were sampled from the system output. These samples included the top-five recommendations for each of nine (9) target researchers whose backgrounds and research interests differed. This sampling approach was used because higher-ranked recommendations are generally the first recommendations reviewed by end users.

Before evaluation of the system's outputs, the recommendations were anonymized by removing all references to the names and email addresses of the researchers and any information that could be used to directly identify them. Three domain experts then independently evaluated each recommendation using a five-point relevance scale, where higher values indicate stronger collaboration relevance. They based their ratings on four criteria: overlap between the research topics, complementarity between the profiles of the researchers, plausibility of future collaboration, and usefulness of the explanation provided by the system. Recommendations with an average expert rating of 4 or 5 were considered relevant.

The results in Table 4 indicate that the proposed recommendation mechanism generated relevant collaboration suggestions. The mean relevance score of 4.28 shows that the recommendations were generally judged between relevant and highly relevant by the expert evaluators. In addition, 40 out of 45 recommendations were rated as relevant or highly relevant, resulting in a relevant recommendation percentage of 88.9%. This indicates that the proposed mechanism was able to identify collaboration opportunities that were meaningful from an academic perspective.

The Precision@5 value of 0.89 indicates that most of the top-five recommendations were relevant. This is important because users are more likely to inspect the first few recommendations rather than the full ranked list. The NDCG@5 value of 0.90 further shows that highly relevant recommendations tended to appear near the top of the ranked results. The inter-rater agreement value of 0.82 indicates a high level of consistency among the expert evaluators.

Table 4. Expert-based recommendation evaluation results

Evaluation Measure	Result
Evaluated recommendations	45
Target researchers	9
Number of expert evaluators	3
Rating scale	1-5
Mean relevance score	4.28
Standard deviation	0.64
Recommendations rated 4 or 5	40/45
Relevant recommendation percentage	88.9%
Precision@5	0.89
NDCG@5	0.90
Inter-rater agreement	0.82

4.5. Baseline Comparison

To determine whether the proposed recommendation mechanism provides value beyond simpler retrieval methods, the results were compared with three baselines: keyword overlap, BM25, and dense-embedding similarity. The keyword baseline ranks candidates using direct keyword overlap. BM25 uses lexical matching over researcher-profile text. The dense-embedding baseline uses cosine similarity between profile embeddings only. In contrast, the proposed method combines semantic retrieval, shared-topic evidence, publication-profile compatibility, institutional context, and structured AI-enrichment outputs.

The same evaluation setting was used for all methods. For each of the nine target researchers, the top-five recommendations generated by each baseline and by the proposed method were evaluated using the same expert-based relevance procedure. Table 5 shows the comparison between the baselines and the proposed method.

As shown in Table 5, the proposed method produced higher relevance and ranking-quality values than the three baselines. The mean relevance score increased from 3.42 for keyword overlap, 3.68 for BM25, and 3.96 for the dense-embedding baseline to 4.28 for the proposed method. Precision@5 also increased to 0.89, while NDCG@5 increased to 0.90. These results indicate that the full recommendation mechanism provided additional value beyond direct keyword matching, lexical retrieval, and dense similarity alone.

Table 5. Comparison with baseline recommendation methods

Method	Relevance	P@5	NDCG@5
Keyword overlap	3.42	0.61	0.68
BM25	3.68	0.69	0.74
Dense embedding baseline	3.96	0.81	0.84
Proposed method	4.28	0.89	0.90

The increase in Precision@5 indicates that more relevant items appeared within the first five recommendations. The increase in NDCG@5 also indicates better ordering of the recommended items. These results support the use of combined semantic retrieval, shared-topic evidence, publication-profile compatibility, institutional context, and structured explanation, rather than relying on a single retrieval signal.

4.6. Ablation and Sensitivity Analysis

Ablation analysis was used to examine the contribution of the main recommendation components. Table 6 shows the recommendation quality after removing selected components or reducing the system to keyword-only retrieval.

Table 6. Ablation analysis of recommendation components

Variant	Precision@5	NDCG@5
Full proposed method	0.89	0.90
Without generative enrichment	0.81	0.84
Without shared-topic evidence	0.84	0.86
Without project-synthesis output	0.87	0.88
Keyword-only retrieval	0.61	0.68

The ablation results show that the full method retained the highest Precision@5 and NDCG@5 values. Removing the generative enrichment stage reduced both metrics, while removing shared-topic evidence also reduced ranking quality. Removing only the project-synthesis output caused a smaller reduction because the retrieval and explanation signals remained available.

Sensitivity analysis was also used to examine whether recommendation quality changed under different retrieval thresholds, top-k settings, and weighting configurations. Table 7 shows the retrieval and weight-sensitivity results.

The sensitivity results indicate that the evaluated configuration remained stable around the selected retrieval and weighting settings. The 0.55 similarity threshold, top-10 candidate setting, and original weight configuration retained the highest values in the evaluated settings. Nearby retrieval thresholds and alternative weight configurations produced only small changes in Precision@5 and NDCG@5.

Table 7. Sensitivity analysis for retrieval and weight settings

Setting	Precision@5	NDCG@5
Similarity threshold = 0.50	0.86	0.88
Similarity threshold = 0.55	0.89	0.90
Similarity threshold = 0.60	0.87	0.89
Top-5 candidates	0.88	0.89
Top-10 candidates	0.89	0.90
Original weights (w1,w2,w3,w4) = (0.40,0.25,0.20,0.15)	0.89	0.90
Higher semantic weight (0.50,0.20,0.15,0.15)	0.88	0.89
Higher shared-topic weight (0.35,0.35,0.15,0.15)	0.87	0.89
Higher publication-compatibility weight (0.35,0.20,0.30,0.15)	0.88	0.89
Higher institutional-context weight (0.35,0.20,0.15,0.30)	0.86	0.88

4.7. Preliminary User Acceptance Assessment

A preliminary user-acceptance assessment was conducted using the System Usability Scale. The assessment was used to examine whether the platform interface and recommendation outputs were usable for institutional research-discovery tasks. Table 8 shows the SUS results.

The mean SUS score indicates acceptable perceived usability for the evaluated interface. This result supports the practical use of the role-based dashboards and explanation-oriented recommendation outputs, while broader longitudinal evaluation remains a direction for future work.

Table 8. System usability scale results

Measure	Result
Participants	15
Mean SUS score	78.6
Standard deviation	8.4

4.8. Dashboard-based Demonstration

The platform also provides dashboards based on user roles, because researchers, research administrators, and system administrators have different information needs. The dashboards do not only display static data, but also provide interactive views that collect the main scholarly indicators, profile-completion status, publication-quality measures, and collaboration outputs. These views support both research discovery and institutional monitoring.

Figure 2 shows the researcher dashboard, which brings together the researcher's individual profile, ORCID status, Scopus-related indicators, citation counts, publication-quality distribution, recent publications, and suggested collaboration opportunities. By showing these elements in one dashboard, the researcher can review whether the scholarly profile is complete, follow the visibility of publications, and notice possible areas that may need improvement. The dashboard

also makes it easier to identify possible collaborators within the institution without searching separately in ORCID records, Scopus-related data, or the internal university records.

Figure 3 shows the explainable collaboration recommendation interface, including ranked collaboration opportunities, similarity values, shared topics, recommendation rationale, suggested project ideas, and first collaboration steps.

The interface converts the generated recommendation fields into a readable format for researchers. Instead of presenting only a numerical ranking, the system explains why a specific researcher pair may be suitable for collaboration and provides a practical starting point for developing a joint research direction.

Figure 4 shows an institutional analytics dashboard for research administrators to show the institutional indicators in one place, such as total users, ORCID coverage, Scopus coverage, total citations, ranked publications, Q1–Q4 publication distribution, department-level indicators, and system-level quality alerts. This provides the opportunity for research administrators to monitor the overall research activity of the institution and identify areas where profile completion, publication quality, Scopus coverage, ORCID linking, and internal collaboration opportunities can be improved.

The dashboard-based results confirm that the proposed platform can support both individual and institutional research needs. At the individual level, it helps researchers understand their scholarly profiles, track their publication indicators, and discover potential collaborators. At the institutional level, it supports research administrators in monitoring research coverage, publication quality, and collaboration opportunities across departments and faculties.

At the system level, administrators can track account completeness, synchronization status, unranked publications, missing profile information, and other data-quality issues. Therefore, the dashboard-based results demonstrate that the

proposed platform provides a practical bridge between scholarly data integration, explainable collaboration recommendation, and institutional research-performance monitoring.

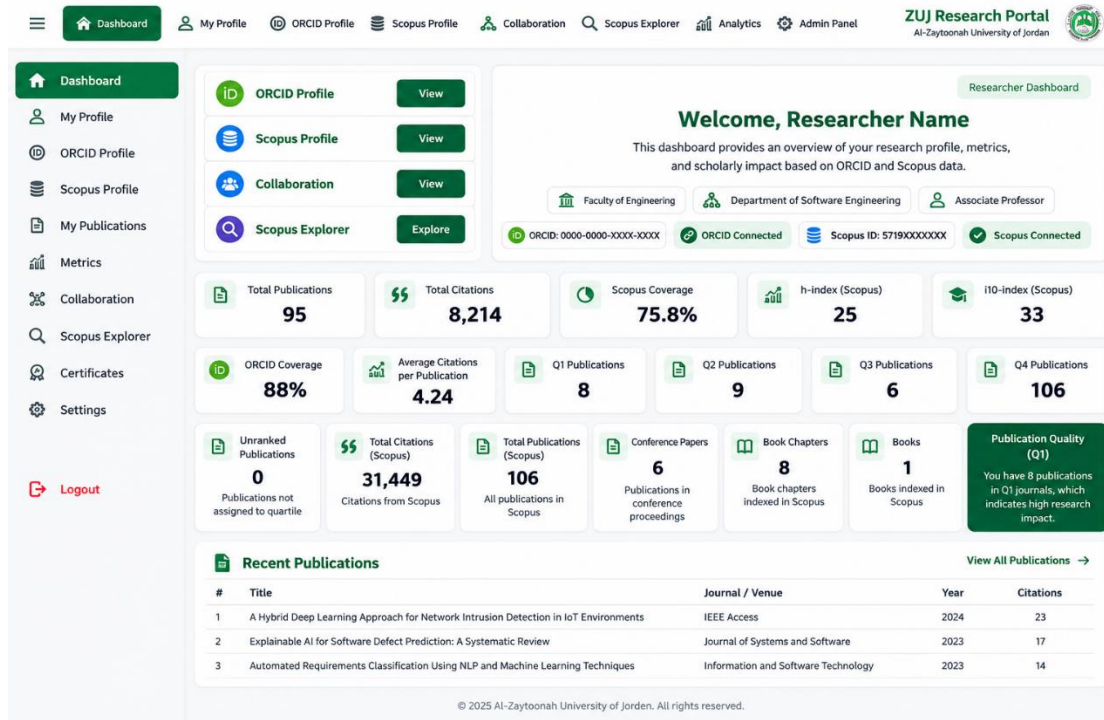


Fig. 2 Researcher dashboard showing unified ORCID and Scopus-related research indicators

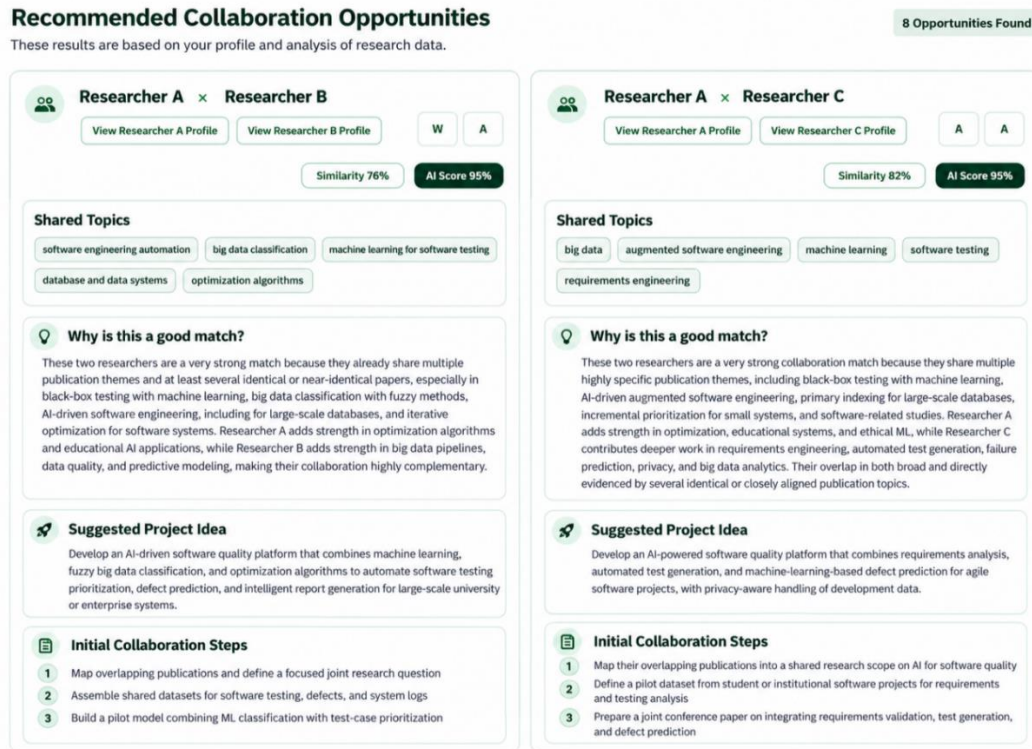


Fig. 3 Explainable collaboration recommendation interface



Fig. 4 Institutional analytics dashboard for research administrators

4.9. Discussion of Findings

The case study illustrates how the proposed system provides a practical method for creating a structured Enterprise Research Network from disparate research record collections. The most important result of this proposed system was its capability to combine three different types of data within one integrated environment. These data types included researcher identification information, scholarly indicators, and semantic collaboration signals. These three types of data were combined in a way that enables the system to go beyond simple profile display and generate actionable collaboration suggestions.

The institutional statistics show that ORCID and Scopus coverage can be tracked directly through the system. Incomplete or disconnected researcher profiles can reduce both the visibility and consistency of institutional research outputs. Therefore, by identifying coverage gaps, the system allows research administrators to encourage profile completion and improve the quality of institutional research records.

Evaluation by domain experts showed that the recommendations were judged as meaningful by the evaluators. The mean relevance score, Precision@5, and NDCG@5 values indicate that the system was able to identify collaboration opportunities that aligned with research interests and plausible directions for academic collaboration. The inter-rater agreement also supports the consistency of the expert judgments.

The baseline comparison supports the added value of the proposed recommendation mechanism compared with simpler retrieval methods. The keyword-overlap and BM25 baselines produced appropriate matches when researchers used similar terminology. The dense-embedding baseline improved over lexical methods, but it did not include shared-topic evidence, institutional context, or structured explanation. The proposed method scored higher in both relevance and ranking quality, indicating that the combined design was more suitable for the evaluated institutional collaboration task.

The explainable component of the application added practical value. A single number is limited for academic collaboration decisions. Displaying common topics, similarity indicators, recommendation rationale, a suggested project idea, and first collaboration steps provides clearer information for researchers. The preliminary SUS result also indicates that the interface was usable for the evaluated research-discovery task.

Overall, the results of the case study and evaluation indicate the feasibility of the proposed architecture for supporting institutional research discovery, collaboration planning, and research-performance monitoring. The evaluation results should still be viewed with some limitations. First, the case study was conducted within a single academic institution. Second, the expert-based evaluation was applied to a selected sample of generated recommendations. Third, the user-acceptance assessment

was preliminary. Future studies could expand the scope to additional institutions, increase the number of recommendations evaluated by experts, collect broader user-based feedback, and assess whether system-identified potential collaborators lead to actual research collaborations over time.

5. Conclusion

This paper introduced an explainable semantic enterprise research network for institutional collaboration recommendation. Internal university records, ORCID-linked data, and Scopus-related scholarly indicators were integrated into one research intelligence platform. Researcher profiles were constructed from publication metadata, keywords, research topics, citation indicators, publication-quality measures, and institutional attributes.

The system used text-embedding-3-small for semantic profile representation, cosine similarity for candidate retrieval, and structured AI-enrichment for explanation and project-synthesis outputs. The case study was conducted in a real university environment with 89 users, including 86 teaching and research staff. The platform also provided aggregated institutional indicators such as ORCID coverage, Scopus coverage, total citations, ranked publications, Q1-Q4 publication distribution, and identified collaboration opportunities. The expert-based evaluation covered 45 recommendations for 9 target researchers and showed a mean relevance score of 4.28, Precision@5 of 0.89, and NDCG@5 of 0.90. The proposed method also produced higher relevance and ranking-quality values than keyword-overlap, BM25, and dense-embedding baselines. Ablation and

sensitivity analyses indicated that the full method retained the highest ranking quality in the evaluated settings. A preliminary SUS assessment with 15 users produced a mean score of 78.6. These results indicate that semantic profiling, institutional indicators, and explainable recommendations can support internal collaboration discovery and research monitoring. Future work will expand the evaluation to include more institutions, larger user samples, and longitudinal analysis of whether recommendations lead to actual collaboration outcomes.

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