An Integrated Approach to Research Paper and Expertise Recommendation in Academic Research

Charles N. Mabude[1], Iyabo O. Awoyelu[2], Bodunde O. Akinyemi[3], Ganiyu A. Aderounmu[4]
Department of Information Systems and Technology, Kings University, Nigeria[1]
Department of Computer Science and Engineering, Obafemi Awolowo University, Nigeria[2, 3, 4]

***Abstract*—Research papers and expertise recommendation systems have been operating independently of one another, resulting in avoidable search queries and unsatisfactory recommendations. This study developed an integrated recommendation system to harmonize research papers and expertise recommendations in the academic domain for enhanced research collaboration. It aims to address issues related to the isolated existence of these systems. A recommendation algorithm was developed to synergize the research paper and expertise recommendation models. The Cosine similarity function between user query and available research papers as well as experts, was combined with selected criteria to achieve recommendation. The synergized model was simulated and evaluated using Precision, Recall, F-measure and Root Mean Square Error as performance metrics. The findings showed that the harmonization of research paper and expertise recommendation approaches provides a holistic and enhanced approach towards research paper and expertise recommendation. Thus, academic researchers now have a reliable way to recommend experts and research papers, which will lead to more collaborative research activities.**

Keywords—Research paper; expertise; recommendation systems; academic

I. Introduction

The ever-increasing growth of data has resulted in the discovery of new research areas within the computer science field, among which is recommender systems. As the amount of available data grows, the problem of managing the information becomes more difficult, which culminates in information overload. The need to address the challenges associated with information overload led to research on information filtering. The Recommender system, as a subclass of the Information Filtering System, is a completely automated system that analyzes users' preferences and predicts users' behaviors. The research interest in recommender systems is still very high, perhaps due to the practical significance of recommendation tasks. Recommender systems collect various kinds of data to create their recommendations [1].

An Expertise Recommender (ER) system offers a means by which scarce resources, in the form of human experts, can be identified and accessed [2]. It is a system designed to facilitate identifying individuals who have the necessary expertise to solve a specific problem [3] [4]. In systems for recommendation of human expertise, the interest is "expert" instead of items [5] [6] like movies or books, as in the case of other recommender systems. Mobile agent technology is one of the approaches that have been implemented for expertise recommendation [7] [8] [9]. Available literature has shown recommendation systems for human expertise to be a valuable instrument incredibly, crucial in scholarly research for managing knowledge.

Research Paper Recommender (RPR) systems have emerged to ease the problem of finding publications relating to researchers' areas of interest [10] and are designed to offer the right publication to the right researcher in the right way. Thus, some users may be interested in the works (research papers or publications) of the expert (researcher) rather than the expert. This is reflected in the search for a research paper (i.e., documented knowledge of the expert) without necessarily being interested in the researcher (expert).

These two aspects of recommender systems are utilized within the academic research domain. The research papers and expertise recommender systems have greatly contributed to improving research collaborations in academia by bridging the knowledge and physical distance among researchers. However, it is mostly the case that a researcher in a particular domain must have either directly or indirectly interacted with one or more researchers in the research domain or certainly perused many research publications in order to elicit knowledge about a particular research project. These publications might be from the researcher (s) that has been directly interacted with or from different researchers.

The success of the recommender system in academics as a tool for collaboration in research is evident in the literature. In recent years, a detached approach to the issues of a research paper and expertise recommendation has existed. However, the academic research concept requires that a researcher be exposed to both direct and indirect contributions of fellow researchers for acceptable research output. The existing expertise recommender systems have not considered using explanations for more details about the researchers' expertise, while the research paper counterpart considered concept similarity of articles without the methods, which resulted in a misleading and unsatisfactory recommendation. Furthermore, both systems experience sparse ratings and function independently, thus, providing partial information about the same academic domain, thereby causing avoidable search queries. There is a need for a holistic approach rather than the current separate approach to expertise and research paper recommendations in academics, and also a system that will harmonize the concept or method similarity of research papers and explanation-based expertise recommendations for an enhanced recommendation.

Thus, in this paper, an attempt is made to concurrently address expertise recommendation and research paper recommendation in a unified recommender system using an integrated recommendation concept. The remaining sections of the paper are organized as follows: Section II discusses the related works while the methodologies applied to achieve the desired results are presented in Section III. The results obtained as well as the interpretations are presented in Section IV. The conclusion of the study is contained in Section V and future work is presented in Section VI.

II. Related Work

There are numerous works in the areas of expertise and research paper recommendations. A survey of available literature on research expertise recommendations shows that academic research expertise systems are less common. However, the increase in available data on academics and their publications has sustained research in the area.

In several researches, a recommender system was developed based on expert and item category by extending recommendations beyond the frequency of rating from users [11] to using trust-aware social web service recommendations mechanisms [12], a triangulated approach[2], bi-directional feedback approach [13] [14], ontology based approach [15], social network-based approach [16], [17], [18], Clustering analysis approach, expertise modeling [19], Knowledge-based approach [20], graph-based approach [21] Citation network graph approach [22] [23] [24], random walk graph approach [25], Content Based Filtering and Collaborative Filtering concepts [26], and association rule approach [27] with the aim of improving the accuracy of the expert recommendation predictions. The factors of topic relevance, expert quality, and researcher connectivity are considered useful in recommending experts in the science-based research community. For example, researcher modeling approach was applied to recommend experts in scientific communities in [28], a co-author recommendation based on powerful and similar peers that suggests future co-authors for scientific article writing was also proposed in [29]. However, these approaches did not address rating sparsity and cold start problem efficiently.

On the other hand, research paper recommendations are another area that is well explored. Nowadays, much of the world's new knowledge is largely captured in digital form and archived within a digital library system. Also, a huge number of academic papers are constantly being published through several conferences and journals. These trends lead to information overload, where users find an overwhelming number of publications that match their search queries but are largely irrelevant to their latent information needs [30]. Thus, most researchers rely on key-based search or browsing through proceedings of top conferences and journals to find their articles of interest [31]. However, according to [10], the challenge is not just to provide researchers with very rich publications at any time, any place, and in any form, but to also offer the right publication to the right researcher in the right way. To achieve this crucial objective, several researchers have initiated some novel approaches depending on their perspectives. Some of the recommendation approaches in the literatures are set theory and graph theory concepts [32] [33] [34], user's preferences, user's requirements and opinion mining approach [30], [35], [36], [37], content-based approach [38], [39], collaborative filtering approach[10] [31] [40], source-independent framework [41], tagging approach [42] and algorithms like an unsupervised algorithm called Paragraph Vector [43], shortest paths algorithm [44], that provide personalized research papers recommendations regardless of the research field and regardless of the user's expertise.

It was observed in all of these approaches that an atomistic approach was being used to address issues related to the research paper and expertise recommendation in the same academic domain, whereas the academic system requires a researcher to be exposed to both direct and indirect contributions of fellow researchers in order to produce acceptable research output. The need to alleviate the challenges of the current isolated approach to research paper and expertise recommendation necessitated this study.

III. Methodology

In this study, the focus was to improve the existing expertise and research paper recommendation models and, as well, synergize them for better recommendations in academics. The details provided in the expertise recommendation part of the integrated system will assist expertise seekers by providing more details about the available experts to guide their choice among recommended experts. Also, in addition to the existing concept semantics-based research paper recommendation, the study will reduce the chances of recommending the wrong research paper to users by combining the concept semantics with the method semantics of research publications to build similarity between research papers for improved recommendation.

In this study, the following research questions were addressed:

- How could the expertise recommendation be enhanced by incorporating explanation to provide more details about the experts' knowledge?
- How could the research paper recommendation be enhanced by combining semantic relationships between concepts and methods used in a research paper?
- How could recommendations be enhanced by synergizing (i) and (ii) above, since both deal with recommendations for the same academic domain?

A. Conceptual Model

The developed model was conceptualized on the basis of building a synergy between two independent but related recommender systems. The improvements are presented as follows.

1) Proposed expertise recommendation model: The existing ER with user classification [13] is being improved by incorporating explainable recommendations to provide further details about the depth of knowledge and research interests of the experts for more effective and persuasive recommendations. The conceptual view of the proposed expertise recommendation approach, presented in Fig. 1, demonstrates the search query as the key input to the system. The search query gets processed through matching with the available experts in the database based on relevance. This is carried out in the "Query/Expertise Matching" section by searching through the database of experts. However, in the database of experts, the experts are classified according to their academic qualifications, which help to differentiate their level of knowledge. An explanation which contains a summary of available information about the knowledge depth and research interests of each expert is generated for each expert using the recommendation logic while the experts are clustered using the tag-based K-Means clustering algorithm. The "Recommendation" segment then presents a list of experts with explanations arising from the calculations in the "Recommendation Logic" segment through computation of the likeness cosine linking the user query with the available data in the target database.

2) Proposed research paper recommendation model: The existing concept-based research paper recommendation system [37] is also being improved by incorporating similarity between methods applied by researchers to solve problems as published in journals. This is because it considers that each published research article consists of two major parts – the concept and the method (s) employed to actualize the concept. Thus, the deficiency of the existing system is addressed by incorporating the similarity in the methods used to solve the problem identified in the research publications into the existing concept-based approach as shown in Fig. 2. The figure shows the search query section where the user inputs keywords relating to the desired research paper. The user's query is then processed by matching it with the available research papers in the database. The recommendation logic is then applied to generate a list of suitable research papers using the tag-based K-Means clustering algorithm. The user then views the recommendation list.

3) The developed integrated recommendation framework: It was observed that though the systems for research papers and expertise recommendation currently exist independently, the dataset utilized in either case is about the same domain, i.e., the academic domain. For instance, expertise recommender systems make use of datasets of published research papers to build the expertise domain of the experts by extracting relevant texts from the publications. Therefore, the two recommended systems are synergized as presented in Fig. 3, which shows that the dataset is pre-processed and loaded into the database. The user profile is created during the first access to the system. Subsequent access requires only the login information of the user, which is entered through "User Info". The "User Identifier" authenticates the user using available user profile information in the database. Once the user is authenticated, the user can then search for the desired information through the "User Query" section. The user query is then processed by applying the cosine similarity function to determine the available experts and research papers in the desired area as specified in the user query. If the user query is available, then the "Recommendation Logic" segment is activated to perform tag-based K-Means clustering of experts and research papers, matrix factorization, and generation of details for the recommendation. The result of this segment is then pushed to the "Recommendation" segment where the list of recommended experts with details and the list of recommended research papers are displayed.

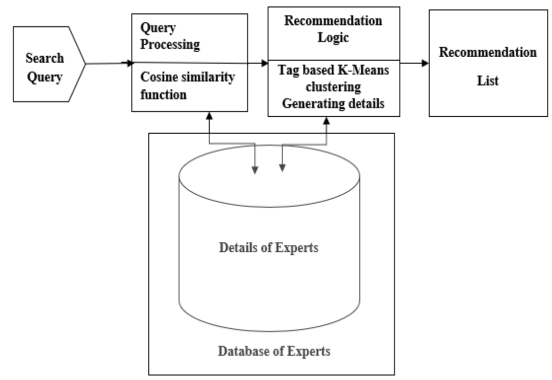

Fig. 1. Improved Expertise Recommendation System.

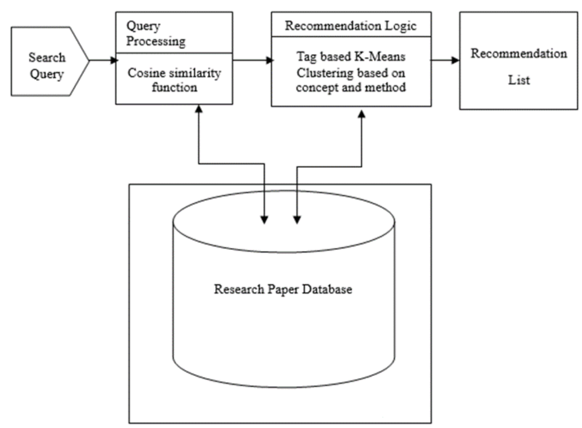

Fig. 2. Improved Research Paper Recommendation System.

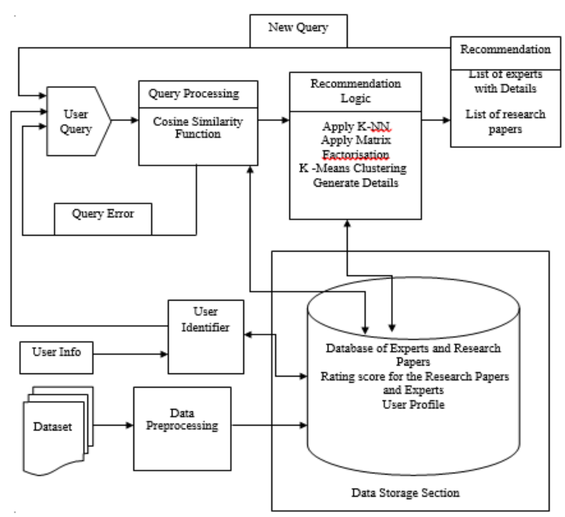

Fig. 3. Proposed Integrated Expert and Research Paper Recommender System.

B. Mathematical Formulation of the Developed Model

The developed model was formulated on the basis of building a synergy between two related sets to achieve a common goal. The related sets considered in this study are a set of experts, i.e., researchers, and a set of research papers, as presented in Equation 1 and Equation 2, respectively. The reviewed literature shows that there are certain features and criteria for expertise and research paper recommendation. A few of the attributes include quantity of publications for target expert, number of citations for target research paper, and user rating, while the criteria for recommendation constitute a combination of selected features.

$$E = \{e_1, e_2, e_3, \dots, e_n\} \tag{1}$$

$$R = \{r_1, r_2, r_3, \dots, r_n\} \tag{2}$$

where

E represents the set of experts and *R* represents the set of n distinct research papers $r_1\ to\ r_n$ while $e_1\ to\ e_n$ represent distinct experts.

Since the dataset of published articles is also utilized for research paper recommendation, in which case, keywords or key phrases from the publications are extracted for the purpose of recommendation, this study therefore considers the possibility of bridging the two independent but related recommendation systems and approaches in order to synergize both systems for enhanced recommendation. To achieve the synergy, the information theory of synergy and the set theory are applied. The set of experts and the set of research papers are then combined into a unified set as presented in Equation 3 and Equation 4, respectively.

$$D = E \otimes R \tag{3}$$

This implies that:

$$D = \{(x, y) \mid for\ all\ x \in E, y \in R\} \tag{4}$$

Therefore:

$$D = \{(e_1, r_1), (e_2, r_2), \dots, (e_n, r_n)\} \tag{5}$$

$E,\ R, e_1\ to\ e_n$ and $r_1\ to\ r_n$, retain their previous meanings while *D* represents the unified set.

Applying the information theory of synergy, the set of experts, "E", can be viewed as variable X_1 while the set of research papers "R" is variable X_2. These two related sets are then combined to form the unified set "D" of research papers and experts, which is represented by the third variable "Y".

Furthermore, the recommendation for the experts is achieved by calculating the impact of the expert in the chosen research area using Equation 6 while incorporating the rating function presented in Equation 7. The impact of an academic researcher in a particular domain obtained through research publications could be helpful for profiling the research expertise or experience of tertiary institutions and other academic institutes, either for the purpose of appointment, collaboration or consultancy.

$$E_{impact} = \sum_{i=1}^{n} \frac{1}{i}\left(\frac{1}{T_p}\left(N_{(cp)^I} + N_{(jp)^I} + N_{c^I}\right) + (A_{re})^I\right) \tag{6}$$

such that;

$$(A_{re})^I = \frac{R_e, i}{N_u, i} \tag{7}$$

where;

In Equation 6, the number of years of experience through research publication is represented by "i", which ranges from 1 to n, where the value of "n" is determined by the user. N_{cp} signifies the quantity of conference articles the expert has published, while N_{jp} signifies the quantity of journal articles the expert has published within the interval of years specified by the user. T_P is the total number of publications by the expert within the specified period, which is the addition of N_{cp} and N_{jp}. N_c represents the number of citations for the papers published by the expert, while T_c represents the total citations of all publications in the area of research publication. $(A_{re})^I$ represents the average rating for each expert over a given year interval. Also, in Equation 7, A_{re} retains its meaning in Equation 6, R_e is the total rating for the experts and N_u is number of users that rated the expert.

1) Matrix factorisation: The research paper recommender system and the expertise recommender system are usually associated with rating sparsity, which was addressed using matrix factorisation. In the matrix factorization approach, every item denoted by *i* is linked with a vector $x_i \in K^f$ and every user denoted by *u* is linked with a vector $y_u \in K^f$. The item *i* refers to expert or research paper while K^f represents the features. Given any item denoted by *i*, the components x_i determine the degree to which positive or negative factors are contained in the item. Given any user *u*, the elements of y_u determine the degree of the user's interest in items with high matching positive factors or negative, as the case may be. The resultant dot product, $x_i^T y_u$, reflects the interface between the user denoted by *u* and the item denoted by *i*— the general interest of the user in the features of the item. This sums up the rating for the item denoted by *i* provided by the user denoted by *u*, which is presented as $\hat{r}_{ui}$, resulting in an approximation.

$$\hat{r}_{ui} \cong x_I \cdot y_u \tag{8}$$

2) Model formulation algorithms: Algorithm 1 shows the procedure for developing an integrated research paper and expert recommendation. The algorithm for predicting user ratings using matrix factorization is presented in Algorithm 2, while the algorithm for the K-Means Clustering Algorithm is presented in Algorithm 3.

IV. Result and Discussion

The developed model was simulated and evaluated in Anaconda with Python version 3.7 environment. The Jupyter Notebook was deployed to provide the Graphical User Interface (GUI) for visualizing the data and the results of the simulation process, and Pandas for data manipulation and analysis. Furthermore, Surprise, which is a Python *scikit* for building and analyzing recommender systems that deal with explicit rating data, was also utilized to apply matrix factorization and cosine similarity functions to the dataset. The detailed results are presented as follows.

A. Analysis of the Dataset

The dataset, sourced from the Scopus database used in this study, contained two thousand (2000) documents while the papers with ratings of one (1) and above were one thousand, four hundred and fifty-one (1451) documents. The cross-validation method was used to validate the dataset using the train_test_split of the scikit-learn library. The data was analyzed and divided into two sets- Eighty percent (80%) training and Twenty percent (20%) testing. The number of records in the training dataset was one thousand, one hundred and sixty (1160) while the number of records in the test dataset was two hundred and ninety-one (291). The analysis of the actual dataset used in the study is presented in Fig. 4 and 5. Fig. 4 shows the distribution of ratings over the dataset, where the rating value of 4 (four) appeared most common among the rated publications, while many of the publications had a zero (0) rating. Fig. 5 shows the distribution of articles over the conference proceedings. It shows that articles are more than conference.

The articles are one thousand and two hundred (1,200) while the conference papers are Eight hundred (800).

B. Simulation Results

In order to ascertain the effectiveness of the developed model using the dataset, the Matrix Factorization algorithm was first applied to address sparse ratings. Then the K-Means algorithm was applied to cluster the publications according to their domain of relevance using the ratings. The Cosine similarity algorithm was further applied to generate similarities for the top one hundred (100) publications, considering each publication as a user case as shown in Fig. 6. The time taken to complete the computation of the similarities was 0:00:00.614037 seconds, which implies that the system is capable of delivering recommendations fast. The detailed results are as follows:

1) Simulation results of the existing expertise and research paper recommender systems: Tables I and II show the results of the selected existing models for expertise recommendation [13] and research paper recommendation [37] systems. The table shows the True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) values over ten (10) iterations, where;

- TP implies true positive and represents relevant experts and research papers recommended.
- FN implies false negative and represents irrelevant experts and research papers recommended.
- FP implies false positive and represents relevant experts and research papers not recommended; and
- TN implies false negative and represents irrelevant experts and research papers not recommended.

In Table I, the values for the TP, TN, and FN fluctuated whereas the values for the FP remained constant for all iterations, which suggest that all recommended items were relevant. In Table II, the values for the TP, TN, FP and FN fluctuated, which suggests that the precision is not maximum.

Algorithm 1 Research Paper and Expert Recommendation Pseudocode

Input: $\vec{R}_u$, *User Query*
D, Dataset of Experts & Research papers
Return: *RL, list of recommended research papers & experts*
1. *Begin*
2. *RL* $\leftarrow \varnothing$;
3. $\vec{R}_u \leftarrow \varnothing$;
4. $\vec{R}_v \leftarrow D$;
5. *Prompt* $\vec{R}_u$;
6. *Compute* $Cos\_Sim(u,v) = \frac{\vec{R}_u \bullet \vec{R}_v}{|\vec{R}_u| \bullet |\vec{R}_v|}$;
7. *IF* $\exists\vec{R}_u \notin D$;
8. *RL* $\leftarrow$ *Not available, enter new search;*
9. *IF* $\exists\vec{R}_u \in D$;
10. *Search;*
11. *Run K-Means Algorithm;*
12. *Run Matrix Factorisation and K-NN;*
13. *For each expert in D identified in Line 9; do*
14. *Calculate* $E_{impact} = \sum_{i=1}^{n} \frac{1}{i}\left(\frac{1}{T_p}\left(N_{(cp)^I} + N_{(jp)^I} + N_{c^I}\right) + (A_{re})^I\right)$;
15. *Generate details - "the expert is recommended because he has: "* $+N_{cp}+N_{jp}$ *"conference & Journal publications cited "* $+N_c$ *"with average rating"* $+A_{re}$ *"over the past three years";*
16. *For each research paper in D identified in Line 9; do*
17. *Generate* $(A_{rr})i = \frac{R_r,i}{N_u,i}$ *and* $(N_c)i$;

    Where A_{rr}, *is the average rating for each research paper,* R_r *is the total rating for the research paper and* N_u *is number of users that rated the research paper and i represents interval in years in all cases.*
18. *Return RL;*
19. *End*

Algorithm 2: Rating Prediction Using Matrix Factorization

Input: training matrix Z, the number of features K, Regularization Parameter λ, Learning Rate ε
Output: row related model matrix X and Column related Model Matrix Y

1. Initialize X, Y to uniform real $(0, \frac{1}{\sqrt{k}})$
2. Repeat
3. For random $z_{ij} \epsilon Z$ do
4. Error $\leftarrow X_i * Y_j - V_{ij}$
5. $X_i \leftarrow X_i - \varepsilon(Error.\boldsymbol{Y_j^T} + \lambda X_i)$
6. $Hj \leftarrow Hj - \varepsilon(Error.\boldsymbol{X_j^T} + \lambda Y_j)$
7. End for
8. Until convergence

Algorithm 3: Tag Based K-Means Clustering Algorithm

Input: Target number of clusters K, Dataset of research papers D, Set of tags R_c and R_m,
Output: An assignment of research paper to clusters using tags.

1. Start
2. Initialization: arbitrarily choose K midpoints of cluster C1,C2,C3,…..,Ck
3. Calculate: estimate the space connecting every data position and group midpoints
4. Affectation: allocate the data position to the group midpoint whose space from the group midpoint is least of all the group midpoints.
5. Bring up to date / calculate: Redo calculation of the latest cluster midpoint using
   $\boldsymbol{V_i} = \frac{1}{\alpha_i}\sum_{j=1}^{\alpha_i \in \mathbb{N}} X_i$ where, 'α_i' signifies the amount of data positions in i^{th} group and $\mathbb{N}$ is a set of natural numbers. Redo calculation of the space connecting every data position and latest obtained group midpoints.
6. Discontinue condition: do again the Affectation steep pending when no data position was assigned again.
7. Stop

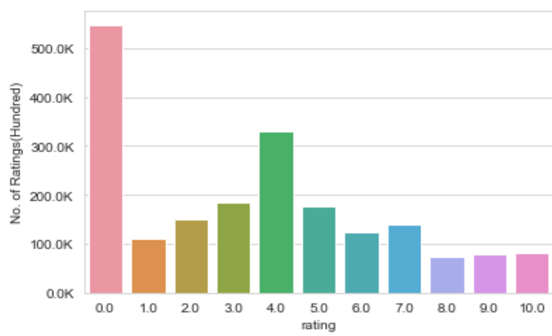

Fig. 4. Distribution of Ratings over Dataset.

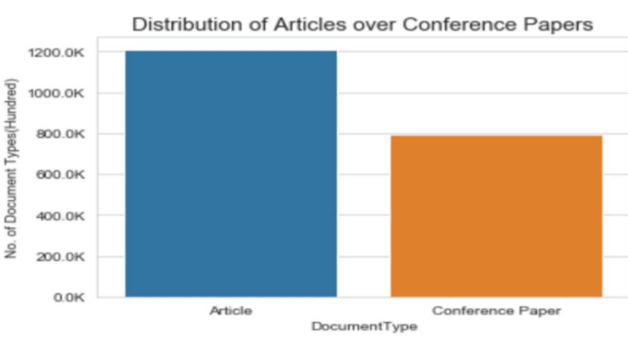

Fig. 5. Distribution of Journal Articles and Conference Proceedings.

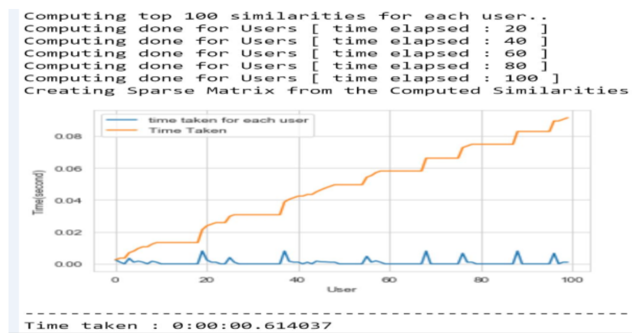

Fig. 6. Cosine Similarity Computation Time for Top 100 Users.

TABLE I. RECOMMENDATION RESULTS OF THE EXISTING EXPERTISE SYSTEM

Iterations	TP	FP	TN	FN
1	93	0	183	15
2	37	0	184	70
3	59	0	199	33
4	89	0	149	53
5	55	0	191	45
6	47	0	189	55
7	68	0	196	27
8	69	0	204	18
9	57	0	186	48
10	46	0	212	33

TABLE II. RECOMMENDATION RESULTS OF THE EXISTING RESEARCH PAPER SYSTEM

Iterations	TP	FP	TN	FN
1	31	27	164	69
2	58	13	178	42
3	33	48	143	67
4	46	43	148	54
5	54	13	178	46
6	86	18	173	14
7	54	23	168	46
8	87	6	185	13
9	88	12	179	12
10	76	5	186	24

The values showed that the existing systems were able to recommend available experts and research papers from the database based on the dataset and the user's query.

2) Simulation results of the developed expertise and research paper recommender systems: Tables III and IV show the results of the developed system for expertise recommendation over ten (10) iterations. The values for the TP and FN fluctuated, whereas the values for the FP and TN remained constant. The results show that the respective developed systems were able to recommend available experts and research papers from the database based on the dataset and the user's query.

3) Simulation results of the developed integrated system: The results of the developed system for the integrated system of Expertise and Research paper recommendation over ten (10) iterations are presented in Table V. The values show the capability of the developed integrated research paper and expertise recommendation system to generate useful sets of research papers and experts according to the user's query. This is in line with the set theory because a collection of expertise and research papers were defined as a set and when the recommendation is zero (0), it implies an empty set. The values are also in line with choice theory because each recommended set of expertise and research papers was based on an assumed user's choice of query using the available keywords in the database.

TABLE III. RECOMMENDATION RESULTS OF THE DEVELOPED EXPERTISE SYSTEM

Iterations	TP	FP	TN	FN
1	93	0	191	7
2	63	0	191	37
3	67	0	191	33
4	45	0	191	55
5	86	0	191	14
6	77	0	191	23
7	92	0	191	8
8	91	0	191	9
9	95	0	191	5
10	73	0	191	27

TABLE IV. RECOMMENDATION RESULTS OF THE DEVELOPED RESEARCH PAPER SYSTEM

Iterations	TP	FP	TN	FN
1	71	0	191	29
2	89	0	191	11
3	87	0	191	13
4	78	0	191	22
5	77	0	191	23
6	92	0	191	8
7	68	0	191	32
8	95	0	191	5
9	94	0	191	6
10	69	0	191	112

TABLE V. RECOMMENDATION RESULTS OF THE DEVELOPED INTEGRATED SYSTEM

Iterations	TP	FP	TN	FN
1	57	7	212	15
2	66	4	161	60
3	42	3	226	20
4	78	3	180	30
5	75	13	147	56
6	97	18	152	24
7	92	23	145	31
8	90	6	172	23
9	89	12	178	12
10	86	5	170	30

C. Evaluation Results

The performances of the existing and developed expertise and research papers recommendation systems were evaluated using precision, recall, F-measure, accuracy, and Root Mean Square Error (RMSE) as follows: The detailed results are as follows:

- Precision shows the recommended system's capacity for showing only relevant experts, while trying to minimize mixing them with irrelevant ones. This is calculated as follows:

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP+FP}} \tag{9}$$

- Recall represents the coverage of relevant experts and research papers that the recommender system can generate. In other words, it measures the capacity of the system to generate all the relevant experts and research papers present in the database. This is calculated as follows:

$$\text{Recall (R)} = \frac{\text{TP}}{\text{TP+FN}} \tag{10}$$

- The recommendation accuracy, which indicates the correctness of the recommendation, is calculated using Equation 11.

$$\text{Accuracy} = \frac{(\text{TP+FN})}{(\text{TP+TN+FP+FN})} \tag{11}$$

- The F-Measure, i.e., the harmonic mean, gives a combined output of both precision and recall for each system. This is calculated as follows:

$$F_1 = 2\frac{X.Y}{X+Y} \tag{12}$$

where X = Precision and Y = Recall.

- The Root Mean Square Error (RMSE) is used to measure the error in the predicted ratings of the recommender system. It is an error in predicting user ratings to address rating sparsity. This is calculated as follows:

$$RMSE = \frac{\sqrt{\sum_{n=1}^{N}(\hat{r}_n - r_n)^2}}{N} \tag{13}$$

Where: $\hat{r}_n$ means the predicted rating while r_n means the true rating. N is the number of rating prediction pairs between the actual data and prediction result.

1) Evaluation of the existing and developed expertise recommendation system: Table VI and Fig. 7, Table VII and Fig. 8 show the evaluation results of the existing and the developed Expertise recommender systems respectively. Both systems gave a constant average precision value of 1.00, which implies that all the recommended experts were relevant. Also, the developed system gave an increase of 17% in average recall value, an increase of 7% in accuracy, an increase of 13% in F-measure, and a decrease of 0.35% in the root mean square error (RMSE) over the existing expertise recommender system. The decreased RMSE value of the developed system implies that there is a wide margin between the minimum and maximum values of the user ratings as contained in the dataset.

TABLE VI. EVALUATION RESULTS OF THE EXISTING EXPERTISE RECOMMENDATION SYSTEM

Iterations	Precision	Recall	Accuracy
1	1	0.86	0.95
2	1	0.35	0.76
3	1	0.64	0.87
4	1	0.63	0.82
5	1	0.55	0.85
6	1	0.46	0.81
7	1	0.72	0.91
8	1	0.79	0.94
9	1	0.54	0.84
10	1	0.58	0.89
Average	**1**	**0.61**	**0.86**
F-measure			**0.75**
RMSE			**2.06**

TABLE VII. EVALUATION RESULTS OF THE DEVELOPED EXPERTISE RECOMMENDATION SYSTEM

Iterations	Precision	Recall	Accuracy
1	1	0.93	0.98
2	1	0.63	0.87
3	1	0.67	0.89
4	1	0.45	0.81
5	1	0.86	0.95
6	1	0.77	0.92
7	1	0.92	0.97
8	1	0.91	0.97
9	1	0.95	0.98
10	1	0.73	0.91
Average	**1**	**0.78**	**0.93**
F-measure			**0.88**
RMSE			**1.71**

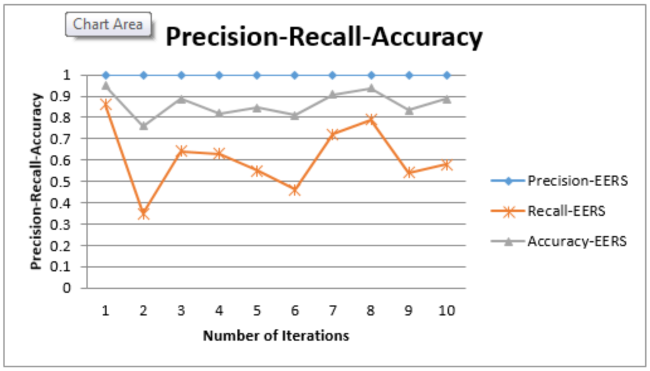

Fig. 7. Evaluation Graph for the Existing Expertise Recommendation System (EERS).

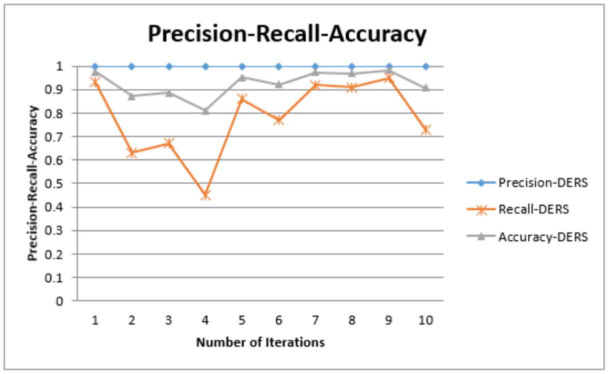

Fig. 8. Evaluation Graph for the Developed Expertise Recommendation System (DERS).

2) Evaluation of the existing and developed research paper recommender systems: Table VIII and Fig. 9, Table IX and Fig. 10, show the evaluation results of the existing and the developed paper recommender system, respectively. The result of the developed system gave an increase of 26% in precision value, an increase of 18% in average recall value, an increase of 12% in accuracy, an increase of 22% in F-measure, and a decrease of 0.47% in the root mean square error (RMSE) over the existing paper recommender system. The decreased RMSE value of the developed system implies that there is a wide margin between the minimum and maximum values of the user ratings as contained in the dataset.

3) Evaluation results of the developed integrated system: Table X and Fig. 11 show the evaluation results of the developed integrated system over ten (10) iterations. The resulted precision value implied that 90% of all the recommended research papers and experts were relevant, which is a very satisfactory performance. The resulted recall value implied that 73% of all relevant research papers and experts were recommended. The resulted accuracy value implied that the correctness of the recommendation was 86%. The resulted F-measure value implied that the combined effect of precision and recall is 81%, which shows that the capability of the developed research paper and expertise recommender system to recommend relevant research papers is very satisfactory. The lower value of 1.69 root mean square error is the effect of matrix factorisation to address rating sparsity.

The results showed that the proposed integrated system performed well based on Precision, Recall, and F-Score and RMSE values. The proposed expertise recommendation component was consistent with the existing system with an average precision value of 1.00, which is an implicit improvement with respect to the recommendation conditions. However, it performed better than the existing system in terms of recall, with average values of 0.61 and 0.76 for the existing and proposed systems respectively, implying a 15% improvement. Furthermore, the proposed research paper recommendation component outperformed the existing system based on precision values by 26% and recall values by 18%. Collectively, the integrated system proved to be reliable by recording appreciable average precision and recall values of ninety percent (90%) and seventy-three percent (73%), respectively, in addition to eighty-one percent (81%) harmonic mean.

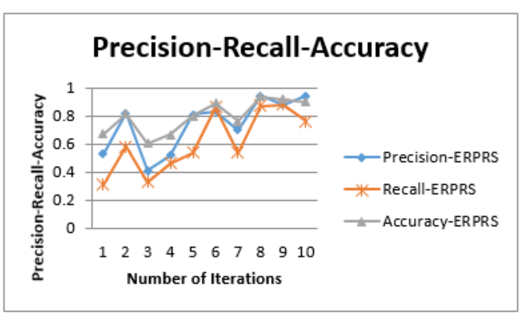

Fig. 9. Evaluation Graph of the Existing Research Paper Recommendation System (ERPRS).

TABLE VIII. EVALUATION RESULTS OF THE EXISTING RESEARCH PAPER RECOMMENDER SYSTEM

Iterations	**Precision**	**Recall**	**Accuracy**
1	0.53	0.31	0.67
2	0.82	0.58	0.81
3	0.41	0.33	0.6
4	0.52	0.46	0.67
5	0.81	0.54	0.8
6	0.83	0.86	0.89
7	0.7	0.54	0.76
8	0.94	0.87	0.93
9	0.88	0.88	0.92
10	0.94	0.76	0.9
Average	**0.74**	**0.61**	**0.80**
F-measure			**0.66**
RMSE			**1.87**

TABLE IX. EVALUATION RESULTS OF THE DEVELOPED RESEARCH PAPER RECOMMENDER SYSTEM

Iterations	**Precision**	**Recall**	**Accuracy**
1	1	0.71	0.9
2	1	0.89	0.96
3	1	0.87	0.96
4	1	0.78	0.92
5	1	0.77	0.92
6	1	0.92	0.97
7	1	0.68	0.89
8	1	0.95	0.98
9	1	0.94	0.98
10	1	0.38	0.7
Average	**1**	**0.79**	**0.92**
F-measure			**0.88**
RMSE			**1.70**

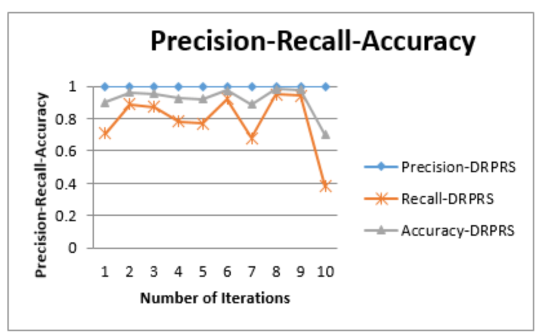

Fig. 10. Evaluation Graph of the Developed Research Paper Recommendation System (DRPRS).

TABLE X. EVALUATION RESULTS OF THE DEVELOPED INTEGRATED SYSTEM

Iterations	Precision	Recall	Accuracy
1	0.89	0.79	0.92
2	0.94	0.52	0.78
3	0.93	0.68	0.92
4	0.96	0.72	0.89
5	0.85	0.57	0.76
6	0.84	0.8	0.86
7	0.8	0.75	0.81
8	0.94	0.8	0.9
9	0.88	0.88	0.92
10	0.95	0.74	0.88
Average	**0.9**	**0.73**	**0.86**
F-measure			**0.81**
RMSE			**1.69**

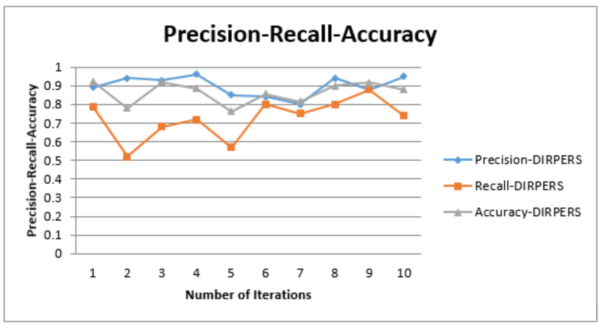

Fig. 11. Precision, Recall and Accuracy Graph for the Developed Integrated System.

V. CONCLUSION

This study has introduced an invaluable means of ensuring reliable recommendation of expertise and research papers in academic research, which would translate into enhanced collaborative research activities among academics. The study concludes that incorporating the similarity of keywords of methods used in carrying out research as reflected in the published research paper to the similarity of keywords of the concept of the research greatly improved the recommendation of relevant research papers. Furthermore, evaluating the expertise of the researchers (experts) using the expert's impact criteria and proving more details about them, also enhanced the recommendation of the relevant experts to the expertise seeker. Finally, the synergized research paper and expertise recommendation system greatly facilitated the simultaneous finding of relevant research papers and experts using a single query, thereby reducing too many avoidable and unnecessary queries, and saving time. Thus, this combined approach to research papers and expertise recommendations is a positive dimension towards achieving great research experience and collaboration among researchers in an academic environment.

VI. FUTURE WORK

The cold start problem continues to surface even as research for a better solution continues. Further studies would consider how to incorporate a reviewer's feedback as an implicit rating to alleviate this challenge in and enhance the results obtained from the matrix factorization method in the research paper recommendation component. The evaluation criteria for expertise will be expanded to make them more robust, while efforts will also be made to create a context-sensitive recommendation for the integration system.

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