Journal of Scientometric Research, 2023; 12(2):480-489.
https://www.jscires.org

Research Article

An Exploratory Study of Scholarly Platforms and Features to Help Emerging Scholars Gain Visibility in the Scholars' Community

Mitali Desai*, **Rupa Mehta**, **Dipti Rana**

Computer Engineering Department, Sardar Vallabhbhai National Institute of Technology, Surat, Gujarat, INDIA.

ABSTRACT

Among available scholarly features on digitized scholarly platforms, certain features have high significance in assessing scholar's influence. If these features are identified, using them legitimately, emerging scholars can increase their influence and gain visibility in the scholars' community. The purpose of this research is to identify and rank significant features on scholarly platforms. To select a data source, a comparative analysis of well-known scholarly platforms is performed. Based on the analysis, ResearchGate (RG) is selected. For RG, this research proposes a methodology to identify and rank significant scholarly features. The results demonstrate that for the rendered RG data, identified significant features in the order of their significance are number of citations, research items, followers, reads, recommendations, followings and projects. Significant features discovered in this research can be employed by various scholarly platforms to identify influential scholars. These scholars can be utilized in applications such as expert finding, influence ranking, recommendation systems, interdisciplinary collaborations etc. Moreover, the identified significant features will help scholars in focusing on certain aspects (features) to increase their influence legitimately.

Keywords: Scholarly platforms, Scholarly features, Influence assessment, Feature ranking, ResearchGate.

Correspondence:
Mitali Desai
Computer Engineering Department, Sardar Vallabhbhai National Institute of Technology, Surat-07, Gujarat, INDIA.
Email: mitalidesai17@gmail.com

Received: 13-06-2022;
Revised: 03-02-2023;
Accepted: 06-04-2023.

INTRODUCTION

The information present across scholarly platforms such as ResearchGate (RG), Google Scholar (GS), Academia.edu, Mendeley and Publons serves a potential base for numerous applications such as expert finding, topical authority finding, community detection, recommendation system etc. in scholarly domain.[1,2] Identifying influential scholars is a leading application in scholarly data analytic. Each scholar has a potential to outspread his/her impact across a scholarly network; however, some scholars demonstrate their dominance. These dominant scholars are known as influential.[3] A precise assessment is required to accurately identify influential scholars.[4] Diverse scholarly features such as count of publications, downloads, citations, recommendations, followers, followings, question, answers present on scholarly platforms provide a baseline for this assessment. Based on such features, a cumulative score can be generated and scholars with high scores are acknowledged as influential among others.

DOI: 10.5530/jscires.12.2.044

While considering diverse features for assessment, certain features demonstrate a high degree of significance. Once such features are identified, emerging scholars can focus on these features to maximize their influence and gain visibility in the scholars' community. The scholars with high influence value can be invited for interdisciplinary explorations,[4,5] expert lectures, article reviews, scientific feedback and collaborations[6,7] based on their research domains and expertise. In this regard, influence intensification on extremely utilized scholarly platforms helps in achieving academic as well as professional impact.

This research focuses on identifying and ranking scholarly features that are significant in scholar's assessment. Each scholarly platform has a separate feature set as well as its own user base. For our research, it is required to select a single scholarly platform that has diverse features and a wide user base. Therefore, a comparative analysis of popular scholarly platforms is conducted. The analysis reveals that RG is preferable with respect to our requirements. For RG, this research evaluates its assessment process; and hence, analytically identifies the significance of each RG feature in scholar's assessment. Based on the identified significance, the features are assigned unique ranks.

The remainder of this paper is structured as follows: In Section 2, the related work is depicted. A comparative analysis of scholarly platforms is presented in Section 3. In Section 4, the proposed methodology is demonstrated. The results are depicted along with detailed discussion in Section 5. In Section 6, summary and future work of this research are provided.

Related Work

The focus of this research is on identifying and ranking various scholarly features based on their significance in scholar's influence assessment. The related work emphasizes on the existing influence identification methods and the features used in these methods.

The existing methods to identify influential scholars from widespread research community fall into two categories: network-based measures and statistical measures. In network-based measures, in order to find influential scholars, the collaboration networks[8-16] of scholars are examined. The centrality algorithms such as degree, closeness, betweenness, eigenvector and PageRank are widely applied to evaluate the influence of each scholar in the network.

In statistical measures, the influence of a scholar is calculated through statistical analysis of his/her scientific contributions. *h*-index proposed in 2005 is pioneer in statistical measures.[17] *h*-index measures the influence of a scholar through publication count and citation count. Though H-index is extremely utilized, it suffers from certain limitations: i) it is susceptible to publication time ii) it does not give any further importance to the paper once it receives *h*-index iii) it cannot uniquely measure the influence of a scholar. To resolve these constrains, different measures are proposed since 2005 such *g*-index,[18] *a*-index,[19] h^2-index,[20] *m*-index,[21] *r*-index,[22] *ar*-index,[22] *f*-index,[23] *t*-index,[24] *e*-index,[25] *b*-index,[26] *hg*-index,[27] *n*-index[28] and *x*-index.[29]

All these measures majorly focus on the publications and citations with different prospects. Some other measures proposed from year 2008 to 2020 include other features such as co-authorship,[30] citing authors,[31] citation age,[32] research domains[15,33] and active research span[34] along with publications and citations.

Apart from the features used in existing measures, other features such as count of recommendations, reads, projects, followers, followings, questions and answers available on scholarly platforms are equally important in assessing a scholar. It is essential to identify the significance of these features in calculating scholar's influence. This provides scholars a vision to focus on certain aspects in order to gain increased scientific visibility in the scholars' community. The statistical measures are at the focus of this research. The significant contributions of this paper are as follows:

- To perform a comparative analysis of RG, GS, Mendeley, Academia.edu and Publons with respect to
    - their adoption and utilization among scholars
    - range and diversity of provided features
- To develop a methodology for RG to
    - identify the significance of RG features based on their contribution in RG scholar's influence assessment
    - generate ranks for significant features based on their identified significance

Comparative Analysis of the Scholarly Platforms

Five well-known scholarly platforms i.e., RG, GS, Mendeley, Academia.edu and Publons are analyzed with respect to their i) adoption and utilization ii) range and diversity of features.

Which scholarly platform is widely adopted and highly utilized?

Various analysis is conducted on scholarly platforms to identify their popularity in terms of total registered profiles, usage frequency and degree of activeness. Analysis was conducted on the distribution of Spanish National Research Council i.e., CSIC scholars' profiles on Academia.edu, GS and RG.[35] The study discovered the higher utilization of RG among all in terms of number of registered profiles. There were 4001, 2036 and 1156 CSIC scholars' profiles registered on RG, GS and Academia.edu respectively. Survey on Academia.edu, Mendeley, RG, MyScienceWork, Humanities Common, Social Science research Network, Profology and Trellis was carried out to learn their usage frequency.[36] The results showed substantially more frequent usage of RG among all. 26% of RG users were found to be daily users, 41% were weekly users and 18% were using RG at least monthly. In total, 85% of RG users specified using RG at least monthly. Another survey was conducted on Academia.edu, Mendeley and RG to measure the degree of activeness of scholars. The results revealed that RG has received the greatest attention in recent times.[37] A study was carried out offering an overview of established and emerging scholarly platforms i.e., Scopus, Web of Science (WoS), PubMed, RG, GS, Academia.edu, Open Researcher and Contributor Identification (ORCID) and Publons. The results disclosed that RG is a widely utilized platform.[1]

Which scholarly platform provides wide range of diverse features?

For mentioned platforms, no systematic analysis on the scholarly features was found in the literature. Thus, we have analyzed these platforms in detail and conducted an in-depth analysis to measure the range and diversity of features they provide. We have registered our profiles on the mentioned platforms and systematically explored their features.

Various scholarly platforms facilitate scholars to conduct diverse research-oriented activities. These activities include profile registration along with the name, affiliation, location, discipline, department, area of interest/skills/expertise, university/organization and professional biography. Other information such as total count of reads, downloads, citations, followers, followings, co-authors, publications and credit score demonstrate an overall impact of a scholar. Scholars can display their scientific contributions in terms of publications on scholarly platforms. The publication-oriented information incorporates publication title, journals/conferences/books, publication year, co-authors, citations, reads/views, recommendations, downloads, article type, keyword list etc. Each indexed publication further has links to the article file, citing articles, references, similar or recommended articles and registered co-authors' profiles. In many network-based scholarly platforms such as RG and Academia.edu, the links to the registered followers' and followings' profiles of a specific scholar are also available. Specific scholarly platform like Publons measures the impact of reviewers and editors. Links and separate count of the peer reviewed journals and editorial journals in addition to the scholar's publication information are provided on Publons.

All such information can be extracted through various scholarly features. These features are responsible to measure the influence of a scholar on various scholarly platforms. The features offered by RG, GS, Mendeley, Academia.edu and Publons are categorized based on the type of information they provide into four categories: User Demographics, Publication Information, Link Information and Peer Review Information.

In Table 1, the features belonging to each respective category are mentioned. ✓ shows the inclusion while ✕ displays exclusion of a specific feature on a specific platform. In our analysis, the features that are only offered by any specific platform can be considered as unique to that platform. The unique features are highlighted in Table . From thorough analysis, it is concluded that RG is preferable in terms of the mentioned two characteristics. Hence, in this research, a methodology is developed to identify and rank significant features on RG. It is noted that in this research, only user demographic features are considered for ranking as these features incisively contribute into the scholar's influence assessment.

The Proposed Methodology

In this research, a methodology is proposed to identify and rank scholarly features on RG by computing feature-based influence identification. This is useful for scholars to increase their influence legitimately. The list of notations is deliberated in Table 2. The proposed methodology is displayed in Figure 1. It has five tasks: data collection, feature layer generation, feature based influence identification, similarity calculations and feature ranking. The detailed processing steps of the methodology are depicted in Algorithm 1.

In data collection task, 1544 RG scholars working in various research domains of Economics are targeted. The profiles of targeted RG scholars are collected using a web rendering method.[38] The profile information i.e., name, affiliation, department, position, location, publication count, skills count, skills, followers count, followings count, citations count, read count, recommendation count, Q&A count, project count, RGScore and Total Research Interest (TRI) represented in terms of user demographic features are collected. The collected data is pre-processed to avoid missing value glitches and stored in a database.

In feature layer generation task, for each RG scholar, m (m=11) features contributing to influence assessment are selected from collected features. Selected m features (represented by F_i) are assigned IDs and shown in Table 3. These m features constitute the feature layer in the methodology.

In feature-based influence identification task, the significance of each RG feature present in feature layer is identified with respect to the assessment process of RG. For each RG feature, the list of RG scholars who are influential with respect to that feature is identified. The scholars having higher (feature) values are denoted as influential for that feature and are sorted in descending order of their (feature) values. For any feature, scholars obtaining higher position in the list signifies high impact towards that feature. For 11 features, 11 top k lists are generated (represented by IF_{Fi}) as shown in Step 1 of Algorithm 1.

In similarity calculations task, for every feature based top k (k influential RG scholars) list, the results are compared with the top k list generated from RGScore and TRI respectively. RGScore and TRI are two scores of RG to gauge the quantitative assessment of each registered and active RG scholar. RGScore is calculated based on the research in scholar's profile and interaction of other scholars with it. TRI is mentioned as a sum of the research interest for each research item in scholars' profiles. Similarity calculations task is demonstrated in Step 2 of Algorithm 1. The similarity values denote how similar the computed list is to the RGScore and TRI list (represented by I_{RG}).

In feature ranking task, based on the achieved similarity values, respective features are assigned ranks. This task is depicted in Step 3 of Algorithm 1. Higher similarity value denotes higher position of a specific feature in the rank list.

Implementation and Result Analysis

The proposed methodology is implemented on machine with Ubuntu 18.04 LTS (64-bit), 8 GB RAM and Intel Core i7-7700 processor using Python 3.8. The experimentation is performed with four values of k with identical intervals i.e., k=25, 50, 75 and 100. The results for k=25 are discussed here. Table 4 contains the list of identified top 25 influential RG scholars for each feature mentioned in Table .

The following contemplates are inferred from Table .

1. Each column depicts the identified top 25 influential scholars in feature-based influence list of F_i.

Table 1: Feature categorization and feature provision on the scholarly platforms.

Category	Feature	RG	Google Scholar	Mendeley	Academia.edu	Publons
User demographics	Name	✓	✓	✓	✓	✓
	Institute/organization	✓	✓	✓	✓	✓
	Department	✓	✓	✓	✓	✓
	Position	✓	✓	✓	✓	✓
	Location	✓	✓	✓	✓	✓
	Discipline	✓	×	×	×	×
	Followers Count	✓	×	✓	✓	×
	Followings Count	✓	×	✓	✓	×
	RGScore	✓	×	×	×	×
	Total Research Interest (TRI)	✓	×	×	×	×
	Web of science ResearcherID	✓	×	×	×	✓
	ORCID	✓	×	✓	×	✓
	User biography	✓	×	✓	✓	✓
	Total no. of publications	✓	✓	✓	✓	✓
	Publication type (article/ conference/ chapter)	✓	×	×	×	×
	Publication availability in full-text	✓	×	×	×	×
	No. of citations	✓	✓	✓	×	✓
	No. of reads/views	✓	×	×	×	×
	No. of full-text reads	✓	×	×	×	×
	No. of recommendations	✓	×	×	×	×
	No. of projects	✓	×	×	×	×
	No. of questions	✓	×	×	×	×
	No. of answers	✓	×	×	×	×
	List of top co-authors	✓	✓	✓	✓	×
	No. of profile views	✓	×	×	✓	×
	h-index	✓	✓	✓	×	✓
	i10-index	✓	✓	×	×	×
	Top *h* cited research	✓	×	✓	×	×
	No. of verified reviews	✓	×	×	×	✓
	No. of verified editor records	✓	×	×	×	✓
	Research fields/area of interest/skills/ expertise	✓	✓	✓	✓	✓
	Reviewer awards list	✓	×	×	×	✓
	Average citations per publication	✓	×	×	×	✓
	Average citations per year	✓	×	×	×	✓
	Total citations per week/month/year	✓	✓	✓	×	✓
	Total reads per week/month/year	✓	×	✓	×	×
	Total recommendations per week/month/ year	✓	×	×	×	×
	Review to publication ratio	✓	×	×	×	✓
	E-mail based update follow	✓	✓	✓	✓	×
Publication information	Publication title	✓	✓	✓	✓	✓
	Authors	✓	✓	✓	✓	✓
	Journal/conference name	✓	✓	✓	✓	✓
	Publication year	✓	✓	✓	✓	✓

Category	Feature	RG	Google Scholar	Mendeley	Academia.edu	Publons
	DOI	✓	✓	✓	✓	✓
	Citation count per publication	✓	✓	✓	×	✓
	Read count per publication	✓	×	✓	✓	×
	Recommendation count per publication	✓	×	×	×	×
	Publication count per journal	×	×	×	×	✓
	Followed publications	✓	×	×	×	✓
	Followed questions	✓	×	×	×	×
	Recommended publications	✓	×	×	×	×
Link information	Links to citations	✓	✓	✓	×	✓
	Link to registered citing author profiles	✓	×	×	×	×
	Links to publishing journal/conference	×	×	×	×	✓
	Links to publications	✓	×	✓	✓	✓
	Link to publication references	✓	×	✓	×	×
	Link to affiliated institute	✓	✓	×	✓	✓
	Link to research fields/area of interest/ skills/expertise	✓	✓	✓	✓	✓
	Link to similar/recommended similar articles	✓	✓	✓	✓	×
	Link to registered co-author profile	✓	✓	✓	✓	✓
	Link to registered followers' profile	✓	×	✓	✓	×
	Link to registered followings' profile	✓	×	✓	✓	×
	Link to questions	✓	×	×	×	×
	Link to answered question	✓	×	×	×	×
	Links to journals with editor records	×	×	×	×	✓
	Links to journals with editorial board memberships	×	×	×	×	✓
	Links to journals with verified reviews	×	×	×	×	✓
	Link to ORCID profile	✓	×	×	×	✓
	Link to Web of science profile	×	×	×	×	✓
	Link to common discussion groups	×	×	✓	×	×
Peer review information	Journals with editorial board memberships (past + current)	×	×	×	×	✓
	Journals with verified editor records (manuscripts handled as editor) with frequency count per journal	×	×	×	×	✓
	Journals with verified reviews with review count per journal	×	×	×	×	✓

2. The identified influential scholars are ranked from 1 to 25 in the decreasing order of the values of F_i. The higher rank of a scholar R_i for F_i denotes the higher contribution of R_i towards F_i.

3. It is noted that a scholar R_i in dataset having the highest contribution towards a specific feature F_2 has rank 1 (position 1) in the feature-based influence list of F_2. This implies for all features.

4. It is less likely that scholar R_i in dataset having the highest contribution towards a specific feature F_2 will significantly contribute towards others features too.

For example, Myrna M Weissman is assigned rank 2 for features F_3 and F_{11}; rank 5 for features F_1 and F_{10}; rank 15 for feature F_2 and rank 23 for feature F_6. For other features, no significant contribution is found in top 25 experimentation.

For every feature-based influence list (IF_{Fi} where i=1 to 9), the similarity is calculated in comparison with two lists generated based on two features IF_{F10} and IF_{F11}. IF_{F10} and IF_{F11} represent RGScore and TRI respectively. Similarity calculations are done based on the concepts of Tanimoto Coefficient, in which the ratio of the intersecting set to the union set is computed as the

Algorithm 1: SFRRG: Scholarly Features Ranking for RG.

Input: Set of RG Users $U = U_1, U_2, \ldots, U_n$

Set of Extracted Features $F = F_1, F_2, \ldots, F_m$

Output: Rank List $R = R_{F1}, R_{F2}, \ldots, R_{Fm}$ \ where m=11

Step 1: Feature based Influence Identification

for i=1 to m do

IF_{Fi} =Sort (U_{Fi}) \Generate Top k lists of influential users $IF = IF_{F1}, IF_{F2}, \ldots, IF_{Fm}$ where m=11 and $\forall\ F_i \in F$

End for

Step 2: Similarity Calculations

for i=1 to F_p do, where *p*=9

Compute a set of similarity values for each pair $\langle IF_{Fi}, IF_{F10} \rangle$ and $\langle IF_{Fi}, IF_{F11} \rangle$

\ where $IF_{F10,} IF_{F11} \in I_{RG}$

$WIF_{F10} = 0.5^* \ IF_{F10}$ and $WIF_{F11} = IF_{F11}$

\Assign the weights to I_{RG}

Compute a set of weighted similarity values for each pair $\langle IF_{Fi}, WIF_{F10} \rangle$ and $\langle IF_{Fi}, WIF_{F11} \rangle$

\ where $WIF_{F10,} WIF_{F11} \in WI_{RG}$

$ASI_{FRG} = \sum i = 19 \ \langle IF_{Fi}, IF_{F10} \rangle, \langle IF_{Fi}, IF_{F11} \rangle$ \ where $\forall$ i $\in ASI_{FRG}$, i $\in$ [0,1]

\ Generate aggregated similarity values for each IF_{Fi}

$SASI_{FRG}$ = Sort (ASI_{FRG}) \ Generate sorted aggregated similarity values for each IF_{Fi}

End for

Step 3: Feature Ranking

Rank(F_i) = 1 to i \ where i=9, $\forall\ F_i \in F$

\ Assign ranks to each feature in the decreasing order of $SASI_{FRG}$ values corresponding to IF_{Fi}

Table 2: List of notations used in the methodology and SFRRG algorithm.

Notation	Meaning
F_i	i^{th} feature
IF_{Fi}	The list of top k influential RG users based upon i^{th} feature
I_{RG}	The list of top k influential RG users based upon official RG impact score
R_{Fi}	Assigned rank to i^{th} feature
m	Total no. of features used to calculate influence
k	Total no. of entities in influence list
WIF_{Fi}	The list of top k influential RG users based upon weighted i^{th} feature
WI_{RG}	The list of top k influential RG users based upon weighted RG impact score
ASI_{FRG}	Aggregated similarity among top k list generated from feature and RG impact score
$SASI_{FRG}$	Sorted aggregated similarity among top k list generated from feature and RG impact score

Table 3: Features with IDs and attributes constituting feature layer in the methodology.

Feature ID	Feature Attribute
F_1	No. of Research Items
F_2	No. of Reads
F_3	No. of Citations
F_4	No. of Questions
F_5	No. of Answers
F_6	No. of Followers
F_7	No. of Followings
F_8	No. of Projects
F_9	No. of Recommendations
F_{10}	RG Score
F_{11}	Total Research Interest

measure of similarity. As the aim is to calculate how close two lists (sets) are, Tanimoto Coefficient is used to perform similarity calculations.

Table 5 represents the similarity values for every pair of $\langle IF_{Fi}, IF_{F10} \rangle$ and $\langle IF_{Fi}, IF_{F11} \rangle$ for i=1 to 9. Here, IF_{F10} and IF_{F11} are repented as I_{RG} in combine. IF_{Fi} represents the list of identified top 25 influential RG scholars based on feature F_i. Similarity value 1 denotes identical lists whereas value 0 represents no similarity in two lists.

It is observed that top 25 influential RG scholars' list computed based on total no. of research items is 48% similar with top 25 list received based on RGScore whereas it is 33% similar with top 25 list received based on TRI. Top 25 influential RG scholars' list computed based on no. of Reads is 2% similar with both RGScore and TRI lists. For total no. of citations, the generated list is 28% and 9% similar to RGScore and TRI lists respectively. For total no. of followers, the generated list is 18% and 33% similar to RGScore and TRI lists respectively. For total no. of followings, the generated list is 2% similar to TRI list. For total no. of projects, the generated list is 2% similar to RGScore list. For total no. of recommendations, the generated list is 2% and 4% similar to RGScore and TRI lists respectively. For other features, there is no similarity found among the generated lists and RGScore as well as TRI.

Considering the high significance of TRI over RGScore in displaying RG scholar's scientific contribution,[39] the weighted similarity matrix is generated and presented in Table 6. Here, WIF_{F10} and WIF_{F11} represent weighted RGScore and weighted TRI while they are cumulatively labeled as WI_{RG}. Here, $WIF_{F10} = 0.5^*IF_{F10}$ and $WIF_{F11} = IF_{F11}$.

After calculating the weighted similarity for every $\langle IF_{Fi}, WIF_{F10} \rangle$ and $\langle IF_{Fi}, WIF_{F11} \rangle$ (for i=1 to 9) pair, the aggregated similarity i.e., ASI_{FRG} is computed. ASI_{FRG} is computed for each IF_{Fi} by aggregating the weighted similarity values of $\langle IF_{Fi}, WIF_{F10} \rangle$ and $\langle IF_{Fi}, WIF_{F11} \rangle$. The aggregated similarity values lie under the

Table 4: Feature based top 25 influential RG users.

Influence Rank	IF_{F1}	IF_{F2}	IF_{F3}	IF_{F4}	IF_{F5}	IF_{F6}	IF_{F7}	IF_{F8}	IF_{F9}	IF_{F10}	IF_{F11}
1	Clement Allan Tisdell	Charles B Nemeroff	Dennis Charney	Imran, M.,	Yoshinori Shiozawa	Federico Del Giorgio Solfa	Federico Del Giorgio Solfa	Aysit Tansel	Volodymyr Saienko	Tiia Vissak	Dennis Charney
2	Charles B Nemeroff	Federico Del Giorgio Solfa	Myrna M Weissman	Yoshinori Shiozawa	Tiia Vissak	Hashem Pesaran	Даниил Ковалев	Arup Barman	Hanna Tolchieva	J. John Mann	Myrna M Weissman
3	J. John Mann	Russell Smyth	Charles B Nemeroff	Sivapalan Achchuthan	Hengky S H	Ross Levine	Алена Бычкова	Clement Allan Tisdell	Ajay Shukla	Charles B Nemeroff	Charles B Nemeroff
4	Dennis Charney	Ilhan Ozturk	Ross Levine	Choen Krainara	Balázs Kotosz	James Heckman	Ilgar Gurbat oglu Mamedov	Peter Ekamper	Tiia Vissak	Dennis Charney	Ross Levine
5	Myrna M Weissman	Stefan G Hofmann	J. John Mann	Ting Fa Margherita Chang	Giuseppe Laquidara	Ernst Fehr	Алексей Бычков	Oğuz Öcal	Arup Barman	Myrna M Weissman	J. John Mann
6	Richard Bryant	Clement Allan Tisdell	Hashem Pesaran	H. Serkan Akilli	Ting Fa Margherita Chang	Stefan G Hofmann	Riccardo Vecellio Segate	Bruno Lanfranco	Hengky S H	Daniel S Pine	Hashem Pesaran
7	Daniel S Pine	Tiia Vissak	James Heckman	Mohsen Keikhaie	Federico Del Giorgio Solfa	Asli Demirguc-Kunt	Yichuan Zhao	Manfred M. Fischer	H Gin Chong	Richard Bryant	James Heckman
8	Peter C. B. Phillips	Ross Levine	Peter C. B. Phillips	Isaac Sánchez-Juárez	Ehsan Rasoulinezhad	H Gin Chong	Benedikt Herz	Jolanda Van den Berg	Ting Fa Margherita Chang	Boris Birmaher	Peter C. B. Phillips
9	Sten H Vermund	Richard Bryant	Ernst Fehr	Haimanot B. Atinkut	Hubert Escaith	Volodymyr Saienko	Volodymyr Saienko	Volodymyr Saienko	Yoshinori Shiozawa	Kerry Ressler	Ernst Fehr
10	Boris Birmaher	Ali Yassin sheikh Ali	Daniel S Pine	Hengky S H	Arup Barman	Hanna Tolchieva	Hanna Tolchieva	Ajay Shukla	Giuseppe Laquidara	Harry B Greenberg	Daniel S Pine
11	Kerry Ressler	Paul Gilbert	Elhanan Helpman	Francesco Aiello	Imran, M.,	Peter C. B. Phillips	H Gin Chong	Silvia Trifonova	Federico Del Giorgio Solfa	Sten H Vermund	Elhanan Helpman
12	Russell Smyth	George A Bonanno	Boris Birmaher	Arup Barman	Choen Krainara	Charles B Nemeroff	Arup Barman	Yuval Neria	Sule Akkoyunlu	Maria A. Oquendo	Boris Birmaher
13	Caroline O'Nolan	Dennis Charney	Raghuram Rajan	H Gin Chong	Isaac Sánchez-Juárez	Daniel S Pine	Giuseppe Laquidara	Lones Smith	Алексей Бычков	James Douglas Bremner	Tor D Wager
14	Stefan G Hofmann	Arup Barman	Kenneth Rogoff	Ajay Shukla	Said Jaouadi	Arup Barman	Hashem Pesaran	Juliana Isabel Sarmiento Castillo	Алена Бычкова	Israel Liberzon	Raghuram Rajan
15	Harry B Greenberg	Myrna M Weissman	Mark L. Gertler	Thushari Sewwandi	H Gin Chong	Giuseppe Laquidara	Pascal Boettcher	Peter Friedrich	Даниил Ковалев	Stefan G Hofmann	Kenneth Rogoff
16	Hashem Pesaran	David M Clark	Tor D Wager	Giuseppe Laquidara	Kazuo Oie	Paul Gilbert	Kenneth Rogoff	Martin Gaynor	Serhat Yüksel	Tor D Wager	Mark L. Gertler
17	Vernon L. Smith	Paresh Kumar Narayan	James Douglas Bremner	Said Jaouadi	Ajay Shukla	David M Clark	Ajay Shukla	Gordon Wilmsmeier	Choen Krainara	Katie A Mclaughlin	James Douglas Bremner
18	Volodymyr Saienko	Volodymyr Saienko	Asli Demirguc-Kunt	Sizyoongo Munenge	Thomas Lines	Mirac Yazici	Aborlo Gbaraka Kpakol	Stepan Zemtsov	Imran, M.,	Barbara O Rothbaum	Asli Demirguc-Kunt
19	Maria A. Oquendo	Anke Ehlers	Gene M Grossman	Federico Del Giorgio Solfa	Marius Babici	Paresh Kumar Narayan	Isma'Il Tijjani Idris	Annika C Sweetland	Balázs Kotosz	John C Markowitz	Richard Bryant

Influence Rank	IF_{F1}	IF_{F2}	IF_{F3}	IF_{F4}	IF_{F5}	IF_{F6}	IF_{F7}	IF_{F8}	IF_{F9}	IF_{F10}	IF_{F11}
20	Israel Liberzon	Tim Dalgleish	David M Clark	Najibullah Hassanzoy	Najibullah Hassanzoy	Tor D Wager	Tiia Vissak	Evans Osabuohien	Said Jaouadi	Peter C. B. Phillips	David M Clark
21	Sylvester Eijffinger	Barbara O Rothbaum	Richard Bryant	Ehsan Rasoulinezhad	Stephen Matteo Miller	Алена Бычкова	Hengky S H	Musa Dasauki	Hubert Escaith	Arieh Y Shalev	Gene M Grossman
22	Hendrik P. Van Dalen	Boris Birmaher	Harry B Greenberg	Heyd Más	Abdol S. Soofi	Ilgar Gurbat oglu Mamedov	Erdoğan Çiçek	Atakan Durmaz	Hashem Pesaran	Tim Dalgleish	Keywan Riahi
23	James Douglas Bremner	Hashem Pesaran	Keywan Riahi	Dr. Sarhan Soliman	H. Serkan Akilli	Myrna M Weissman	Elchin Suleymanov	Eglantina Hysa	Stefan G Hofmann	Clement Allan Tisdell	Stefan G Hofmann
24	Barbara O Rothbaum	Choen Krainara	Kerry Ressler	James Thomas Bang	Sivapalan Achchuthan	George A Bonanno	Yuval Neria	Orhan Şimşek	Asli Demirguc-Kunt	Ernst Fehr	Harry B Greenberg
25	John C Markowitz	Daniel S Pine	George Akerlof	Tiia Vissak	Takeshi Matsuishi	Tiia Vissak	Takeshi Matsuishi	David Laborde	Ilhan Ozturk	Ricardo Araya	Kerry Ressler

Table 5: Similarity Matrix.

IF_{Fi}	I_{RG}	
	IF_{F10}	IF_{F11}
IF_{F1}	0.48	0.33
IF_{F2}	0.24	0.2
IF_{F3}	0.28	0.92
IF_{F4}	0	0
IF_{F5}	0	0
IF_{F6}	0.18	0.33
IF_{F7}	0	0.02
IF_{F8}	0.02	0
IF_{F9}	0.02	0.04

Table 7: Aggregated Similarity.

IF_{Fi}	ASI_{FRG}
IF_{F1}	0.285
IF_{F2}	0.16
IF_{F3}	0.53
IF_{F4}	0
IF_{F5}	0
IF_{F6}	0.21
IF_{F7}	0.01
IF_{F8}	0.005
IF_{F9}	0.025

Table 6: Weighted Similarity Matrix.

IF_{Fi}	WI_{RG}	
	WIF_{F10}	WIF_{F11}
IF_{F1}	0.24	0.33
IF_{F2}	0.12	0.2
IF_{F3}	0.14	0.92
IF_{F4}	0	0
IF_{F5}	0	0
IF_{F6}	0.09	0.33
IF_{F7}	0	0.02
IF_{F8}	0.01	0
IF_{F9}	0.01	0.04

Table 8: Sorted Aggregated Similarity.

IF_{Fi}	$SASI_{FRG}$
IF_{F3}	0.53
IF_{F1}	0.285
IF_{F6}	0.21
IF_{F2}	0.16
IF_{F8}	0.025
IF_{F4}	0.01
IF_{F5}	0.005
IF_{F7}	0
IF_{F9}	0

Table 9: Identified influential RG features and their assigned ranks.

Feature ID	Feature Attribute	Assigned Ranks
F_3	No. of Citations	1
F_1	No. of Research Items	2
F_6	No. of Followers	3
F_2	No. of Reads	4
F_9	No. of Recommendations	5
F_7	No. of Followings	6
F_8	No. of Project	7

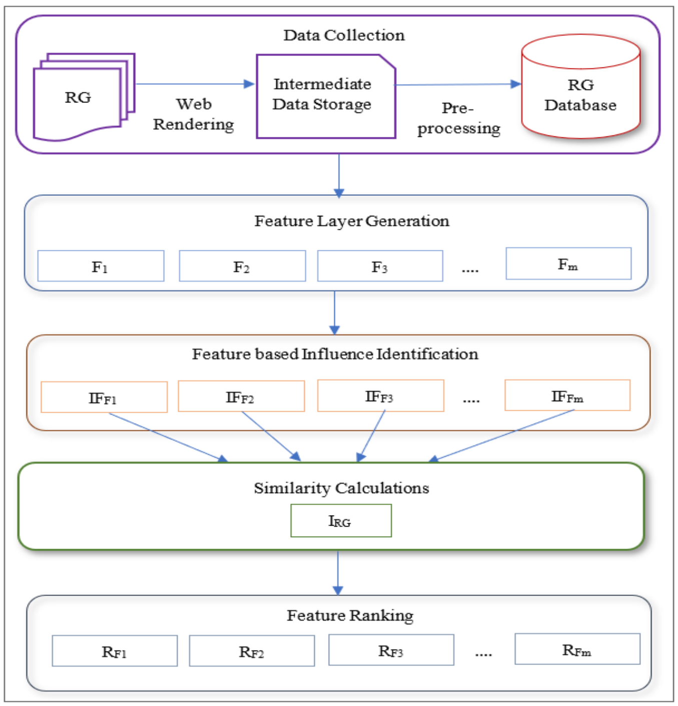

Figure 1: The proposed methodology.

range of [0,1]. For feature ranking, the aggregated similarity values are sorted in decreasing order.

Aggregated and sorted aggregated similarity values are presented in Table 7 and Table 8 respectively.

Based on the sorted aggregated similarity values for each IF_{Fi}, the corresponding feature F_i is assigned a rank. As per Table 9, Rank 1 denotes the highest significance and Rank 7 denotes the lowest significance of a specific feature F_i in assessing RG scholars. As the sorted aggregated similarity values for the number of questions and answers are found to be zero, they are eliminated from our ranking list.

According to the rendered RG data and obtained results for k=25, number of citations, research items, followers, reads, recommendations, followings and projects are identified as significant features in the order of their significance. Other features i.e., number of questions and answers are identified as non-significant.

The same experiment is performed with k=50, 75 and 100. Lists of identified top k influential scholars vary for different values of k; however, the obtained feature ranks are identical.

Leveraging the provided ranked features, emerging RG scholars can legitimately boost their influence and increase their visibility in the scholars' community.

SUMMARY AND FUTURE WORK

In recent times, the scholarly platforms provide a digitized medium to the scholars for performing various research-oriented activities. These scholarly platforms provide various scholarly features such as count of research items, citations, reads, recommendations, projects, questions, answers etc. By applying statistical measures on these features, an assessment score of a scholar can be computed and the scholars having higher score among others can be signified as influential.

All the scholarly features available on scholarly platforms do not imply equal significance in scholar's assessment. To accurately measure the influence of scholars, it is essential to identify the significance of different scholarly features. This will also help scholars to focus more on certain aspects in order to boost their influence in the scholars' community.

This research aims at identifying and ranking the significant scholarly features. For our study, it is required to select a scholarly platform with a wide range of diverse features and higher utilization among others. Thus, a comparative analysis is conducted on well-known platforms i.e., RG, GS, Mendeley, Academia.edu and Publons. The analysis revealed that RG is preferable in terms of our requirements. Thus, taking RG in consideration, a methodology is proposed to identify significant scholarly features and rank them. For the rendered RG data; number of citations, research items, followers, reads, recommendations, followings and projects (in the order of their ranking) are identified as significant features of RG.

In the future, different scholarly platforms can utilize the discovered significant features as weighted features to compute assessment scores to their users. Based on such score(s), influential scholars on scholarly platform(s) can be recognized. Common influential scholars among multiple scholarly platforms can also be recognized. Such scholars can be utilized in realistic applications of scholarly data analytic. Apart from user demographic features explored in this research, the significance of publication, link and peer review-based features can also be identified for RG and other scholarly platforms. In this research, user demographic features of RG are explored. There is a wide scope to identify the significance of publication, link and peer review-based features on RG as well as other scholarly platforms.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

REFERENCES

1. Gasparyan AY, Nurmashev B, Yessirkepov M, Endovitskiy DA, Voronov AA, Kitas GD. Researcher and author profiles: opportunities, advantages, and limitations. Journal of Korean Medical Science. 2017;32(11):1749-56.
2. Ebrahimzadeh S, Rezaei Sharifabadi S, Karbala Aghaie Kamran M, Dalkir K. Triggers and strategies related to the collaborative information-seeking behaviour of researchers in ResearchGate. Online Information Review. 2020;44(5):1077-96. DOI: 10.1108/OIR-12-2019-0380
3. Desai M, Mehta RG, Rana DP. "An empirical analysis to identify the effect of indexing on influence detection using graph databases", International Journal of Innovative Technology and Exploring Engineering. 2019;8(9S):414-21.
4. Wu X, Zhang C. "Finding high-impact interdisciplinary users based on friend discipline distribution in academic social networking sites", Scientometrics, 2019;119(2):1017-35.
5. Bromham L, Dinnage R, Hua X. "Interdisciplinary research has consistently lower funding success".Nature. 2016;534(7609):684-7.
6. Elsayed AM. "The use of academic social networks among Arab researchers: A survey', Social Science Computer Review. 2016;34(3):378-91.
7. Mas-Bleda A, Thelwall M, Kousha K, Aguillo IF. "Do highly cited researchers successfully use the social web? ", Scientometrics. 2014;101(1):337-56.
8. Fiala D, Rousselot F, Jezek K. "PageRank for bibliographic networks", Scientometrics. 2008:76:135-58.
9. Yan E, Ding Y. "Discovering author impact: A PageRank perspective", Information Processing and Management. 2010;47:125-34.
10. Ding Y, Cronin B. "Popular and/or prestigious? measures of scholarly esteem", Information Processing and Management. 2010;47:80-96.
11. Ding Y. "Scientific collaboration and endorsement: Network analysis of coauthorship and citation networks", Journal of Informetric. 2011;5(1):187-203.
12. Gollapalli SD, Mitra P, Giles CL. "Ranking experts using author-document-topic graphs", in Proceedings of the 13th ACM/IEEE-CS Joint Conference on Digital Libraries', JCDL '13, Association for Computing Machinery, New York, NY, USA, 2013; p. 87-96. Doi: 10 1145/2467696 2467707
13. Amjad T, Daud A, Che D, Akram A. "Muice: Mutual influence and citation exclusivity author rank', Information Processing and Management. 2016;52(3):374-86.
14. Amjad T, Daud A, Akram A, Muhammed F. "Impact of mutual influence while ranking authors in a co-authorship network", Kuwait Journal of Science. 2016;43(3):101-9.
15. Amjad T, Daud A. "Indexing of authors according to their domain of expertise", Malaysian Journal of Library and Information Science. 2017;22:69-82.
16. Bibi F, Khan H, Iqbal T, Farooq M, Mehmood I, Nam Y. "Ranking authors in an academic network using social network measures", Applied Sciences. 2018;8:1824.
17. Hirsch JE. "An index to quantify an individual's scientific research output", Proceedings of the National Academy of Sciences. 2005;102(46):16569-72.
18. Egghe L. "An improvement of the *h*-index: The *g*-index", ISSI Newsletter. 2006;2.
19. Rousseau R. New Developments Related to the Hirsch Index. Science Focus. 2006;1(4):23-5..
20. Kosmulski M. MAXPROD: A new index for assessment of the scientific output of an individual, and a comparison with the *h*-index. Cybermetrics: International Journal of Scientometrics, Informetrics and Bibliometrics. 2007(11):5.
21. Burrell Q. "Hirsch's *h*-index: A stochastic model", Journal of Informetrics. 2007;1:16-25.
22. Jin B, Liang L, Rousseau R, Egghe L. "The R-and AR-indices: Complementing the *h*-index", Chinese Science Bulletin. 2007;52.
23. Katsaros D, Akritidis L, Bozanis P, "The f index: Quantifying the impact of coterminal citations on scientists' ranking", Journal of the American Society for Information Science and Technology. 2009;60(5):1051-6.
24. Tol R. "The *h*-index and its alternatives: An application to the 100 most prolific economists", Scientometrics. 2009;80(2):317-24.
25. Zhang C. "The *e*-index, complementing the h-index for excess citations", PLoS One. 2009;4(5).
26. Brown RJ. A simple method for excluding self-citation from the h-index: the b-index. Online Information Review. 2009;33(6):1129-36.
27. Alonso S, Cabrerizo FJ, Herrera-Viedma E, Herrera F. "hg-index: A new index to characterize the scientific output of researchers based on the h-and g-indices", Scientometrics. 2010;82(2):391-400.
28. Namazi MR, Fallahzadeh MK. "Viewpoint n-index: A novel and easily-calculable parameter for comparison of researchers working in different scientific fields", Indian J Dermatol Venereol Leprol. 2010;76(3).
29. Claro J, Costa CA. "A made-to-measure indicator for cross-disciplinary bibliometric ranking of researchers performance", Scientometrics. 2011;86(1):113-23.
30. Harzing AW. "Reflections on the h-index". 2008. Available on: http://www. harzing. com/pop_hindex.htm.
31. Ajiferuke I, Wolfram, D. "Citer analysis as a measure of research impact: Library and information science as a case study", Scientometrics. 2010;83(3):623-38.
32. Harzing AW. "The publish or perish book", 2010. Melbourne, Australia: Tarma Software Research Pvt. Ltd.,
33. Farooq. "Finding the top conferences using novel ranking algorithm", International Journal of Advanced and Applied Sciences. 2017;4(148-52).
34. Hou J, Yang X, Chen C. "Measuring researchers' potential scholarly impact with structural variations: Four types of researchers in information science (1979–2018)". PloS one. 2020;15(6).
35. Ortega JL. "Toward a homogenization of academic social sites: A longitudinal study of profiles in academia. edu, google scholar citations and ResearchGate", Online Information Review. 2017;41(6):812-25.
36. Rapple C. "Understanding and supporting researchers' choices in sharing their publications: the launch of the fairshare network and shareable pdf", Insights. 2018;31.
37. Jordan K. 2019. "From social networks to publishing platforms: a review of the history and scholarship of academic social network sites", in Frontiers in Education. 2019.
38. Desai M, Mehta R, Rana D. "RGNet The Novel Framework to Model Linked ResearchGate Information into Network Using Hierarchical Data Rendering", Springer. 2020;4:37-45.
39. Mason S. "Adoption and usage of academic social networks: a Japan case study'. Scientometrics. 2020;122:1751-67.

Cite this article: Desai M, Mehta RG, Rana DP. An Exploratory Study of Scholarly Platforms and Features to Help Emerging Scholars Gaining Visibility in the Scholars' Community. J Scientometric Res. 2023;12(2):480-9.