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RESEARCH

Knowledge discovery through interpretable decision rules: a framework for ranking researchers from bibliometric data

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Abstract
In the evolving landscape of scholarly evaluation, there is a pressing need for interpretable and data-driven methods to identify high-impact researchers. While platforms such as Google Scholar and Web of Science provide extensive bibliometric metadata such as total publications, citation counts, and h-index values, there remains no universally accepted framework to recognize top-performing academics. This study proposes a structured approach for learning interpretable decision rules from large-scale bibliometric data, aimed at identifying award-worthy researchers. Using a curated dataset of 1180 researchers in the civil engineering domain (590 awardees and 590 non-awardees), we compute 64 quantitative author assessment parameters spanning four categories. Feature importance is ranked using a multilayer perceptron (MLP) with recursive feature elimination, and decision trees are then used to derive transparent rules for researcher recognition. Our framework achieves classification accuracies between 60 and 69% and demonstrates that top-ranked parameters from each category effectively position 25–61% of awardees among the top 100 researchers. The findings offer a scalable and interpretable model for academic impact assessment and contribute to the development of objective recognition systems within the research community.

Keywords Bibliometric data · Author assessment parameters · Feature ranking · Multi-layer perceptron (MLP) · Decision tree rules · Scientometrics · Research impact evaluation

1 Introduction

Millions of researchers contribute to the ever-expanding corpus of scientific literature each year [1, 2]. However, the immediate impact and quality of their contributions often remain

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opaque due to the time required for scholarly recognition. This delay can hinder the timely acknowledgment of deserving individuals, potentially limiting their influence within the broader scientific community. The evaluation of researchers has long been a subject of debate, with various scientific societies adopting diverse criteria for measuring research impact. Despite these efforts, a universally accepted framework for identifying outstanding researchers has yet to emerge.

Numerous methodologies for assessing research impact have been proposed [3–5]. Traditional approaches such as expert reviews, while credible, are resource-intensive and time-consuming. In contrast, quantitative metrics—including total publications and citation counts—are more scalable but present their own limitations. For instance, some researchers may prioritize quantity over quality by publishing in low-impact venues [6], or engage in self-citation to inflate citation metrics artificially [7].

The introduction of the h-index by Hirsch marked a pivotal advancement by integrating both quantity and quality of output into a single metric [8, 9]. Nonetheless, the h-index has inherent shortcomings. For example, increases in citations within the h-core do not necessarily improve the index [10], and papers with similar citation counts may fall outside its scope [11]. To address these issues, numerous alternative metrics have been introduced [12], including the A-index [13], AR-index [14], M-Quotient [15], and k-index [16]. However, many of these metrics have been validated only on limited or hypothetical datasets, raising questions about their generalizability [17].

Evaluations of these alternative indices have produced mixed findings. For instance, Dienes compared the h-index with the g-index and complementary h-index in mathematics [10], while De et al. focused on h-index variants in civil engineering, emphasizing citation intensity and publication age [18]. Schreiber assessed h-index variants using neuroscience data [19], while Ain et al. [17] and Ghani et al. [20] examined citation intensity-based indices in mathematics. Moreira et al. explored performance metrics for civil engineering researchers [21]. More recent studies by Mustafa et al. [22, 23] and Ahmed et al. [2] have further extended this line of research, analyzing parameters such as author count and publication age. Ahmed et al. also introduced dynamic random forests with brute-force optimizers for parameter ranking [5]. Despite these contributions, the field still lacks a transparent and actionable set of rules for systematically evaluating researchers.

This study addresses this gap by formulating interpretable decision rules based on the most impactful bibliometric parameters across four categories: (1) primitive indicators, (2) publication and citation-based metrics, (3) age-adjusted metrics, and (4) author count-based indices. We employ a multilayer perceptron (MLP) classifier with recursive feature elimination (RFE) to rank 64 candidate parameters, selecting the top five from each category for rule generation via decision tree modeling. Experiments are conducted on a domain-specific dataset comprising 590 award-winning researchers and 590 non-awardees in the civil engineering field.

This research is guided by the following questions:

- Which quantitative parameters most effectively distinguish award-winning researchers in each category?
- Which parameter categories yield the most comprehensive rule sets for identifying award recipients?

The study offers meaningful insights for scholars seeking to enhance their academic impact and provides a foundation for standardized, data-driven recognition systems in the scientific community. These insights are operationalized through interpretable decision rules extracted from bibliometric data, which quantify the thresholds and patterns associated with award-winning researchers. These rules derived from top-performing metrics such as Cites per Author, AR Index, and Tapered H Index offer concrete benchmarks that individual researchers can target to enhance their academic visibility. Simultaneously, they provide institutions with a replicable and objective framework for researcher evaluation, enabling scalable and data-driven recognition mechanisms.

It is important to acknowledge that academic awards are not granted solely based on bibliometric indicators. Expert evaluations often consider a combination of factors, including research quality, innovation, leadership, and contributions to the academic community. However, in large-scale assessments or institutional screenings, bibliometric indicators serve as essential tools for shortlisting and benchmarking candidates due to their objectivity and scalability. In this study, we do not claim that bibliometric data alone fully explain award decisions. Instead, we explore whether interpretable decision rules derived from bibliometric features can effectively approximate patterns associated with award-worthy academic profiles. The aim is not to replace expert judgment, but to provide a transparent and data-driven framework that can assist in preliminary evaluations and help understand the structural characteristics of recognized researchers.

The remainder of the paper is structured as follows: *Literature Review*, which summarizes existing research; *Methodology*, detailing the parameter ranking and rule generation approach; *Results*, which present experimental findings; *Conclusion*, which highlights key outcomes; and *Future Work*, which outlines potential research directions.

2 Literature review

In the current scientific landscape, establishing standardized criteria for evaluating researchers' performance is essential to ensure fair and unbiased ranking systems. Commonly used metrics for assessing research impact include the number of publications, citation counts, the h-index and its variations, as well as integrated methodologies. Although researchers are often recognized for their academic and professional achievements through subjective evaluations [24–27], such traditional methods predominantly rely on bibliometric indicators, which may not always be appropriate for comprehensive and equitable global assessments. These metrics have been criticized for their limitations; for example, a researcher with a large number of publications may appear prolific even if their work is published in low-impact venues [28]. Similarly, citation counts can be distorted by self-citation or may reflect negative citations [14].

The h-index, popular for its simplicity and ease of interpretation, also has limitations. It may fail to accurately represent a researcher's influence when citations within the h-core increase [29], and it tends to disadvantage early-career researchers who have not yet had time to accumulate citations. Moreover, the h-index may favor inactive researchers whose earlier work continues to accrue citations [30, 31]. To address these shortcomings, alternative indices—such as the A-index, k-index, and f-index—have been proposed to supplement or refine h-index evaluations.

Recent literature has increasingly focused on evaluating these alternative indices. For instance, Ayaz et al. [12] examined h-index performance using award data from mathematical societies and found it to outperform other metrics. Raheel et al. [32] extended this analysis by incorporating additional h-index variants and reaffirmed the original index's robustness. In the neuroscience field, Ameer et al. [33] highlighted the hg-index and R-index as influential in identifying award-winning researchers. Similarly, Ain et al. [34] analyzed quantitative parameters in the mathematics domain and established parameter rankings correlated with academic recognition. However, that study evaluated awards granted prior to the development of many modern indices, introducing potential bias due to historical context.

To mitigate such limitations, Usman et al. [6] conducted a domain-specific analysis in civil engineering, comparing awardees and non-awardees from the same time period—specifically since 2005—by focusing on those honored by prestigious societies. Nonetheless, the dataset used in that study lacked the statistical power necessary to generalize conclusions about the most impactful parameters. Furthermore, existing literature offers no well-defined criteria for establishing benchmark parameters for systematic researcher evaluation. Alshdadi et al. [7] proposed guidelines for scholarly assessment, though the selected features were limited in scope.

More recently, Mustafa et al. [22, 23] conducted two domain-focused studies to address this gap. The first explored publication and citation-based parameters, identifying the normalized h-index as a top-performing metric. The second study, centered on age-based metrics, found the AR-index to be most effective. Both analyses were grounded in mathematics domain datasets, contributing important, though discipline-specific, insights.

A review of these developments highlights the evolving nature of researcher assessment over the last decade. The focus has shifted from simple citation counts to more complex, contextual metrics—often without robust cross-domain validation. New approaches frequently arise from unconventional models or are tested on limited datasets, complicating comparative evaluation. Thus, a comprehensive, rule-based framework integrating top-ranked metrics is necessary to discern truly impactful researchers. By identifying patterns among award recipients and embedding these insights in transparent rules, it becomes feasible to extend recognition to overlooked yet deserving scholars.

3 Methodology

Building upon the insights gained from the literature review, this study focuses on rule mining to identify high-impact researchers in the civil engineering domain. To determine the most influential quantitative parameters across four categories, we employ a multilayer perceptron (MLP) classifier combined with a recursive feature elimination (RFE) technique. This approach enables efficient feature ranking by leveraging the diverse set of 64 available author assessment parameters.

The overall methodology, illustrated in Fig. 1, comprises the following sequential steps:

(i) Selection of the domain and collection of datasets,
(ii) Computation of author assessment parameters,
(iii) Ranking of parameters based on their predictive importance,
(iv) Prediction of awardees using the top-ranked parameters,
(v) Rule mining based on the top five parameters identified in each category.

In the following subsections, we elaborate on each of these methodological components, detailing the data sources, parameter calculations, feature selection pipeline, and rule generation procedures employed in this study.

3.1 Domain selection and dataset collection

In this study, a domain-specific dataset was required, and the civil engineering domain was chosen due to its extensive history and substantial contributions to research, making

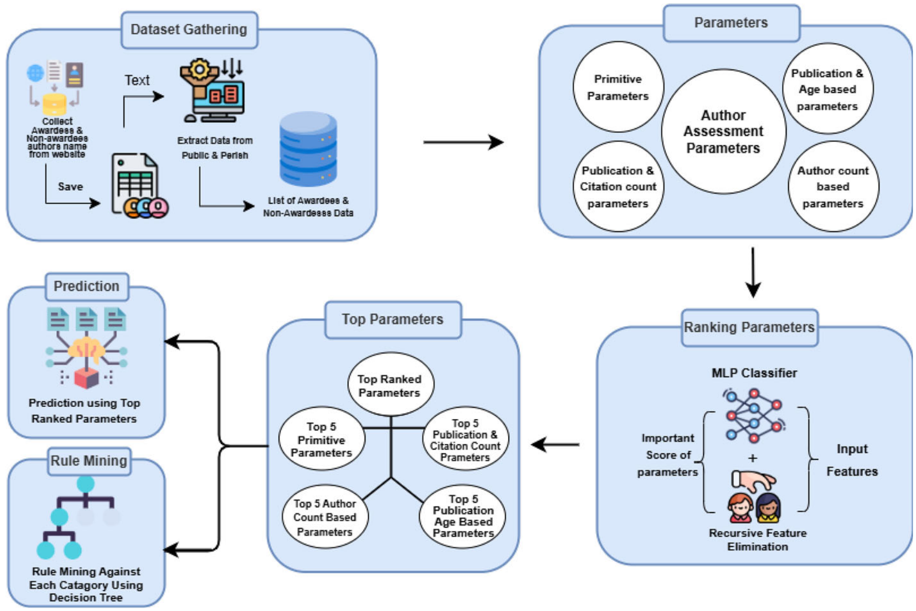

Fig. 1 Architecture diagram of the proposed methodology

it well-suited for evaluating the proposed methodology. This field is notable for recognizing outstanding researchers through annual awards presented by prominent scientific societies, further highlighting the impact of their work. Its broad scope has also made it a frequent subject in prior research [6, 32].

For experimentation, the dataset comprised 1,180 records, evenly divided between 590 awardees and 590 non-awardees. Data for awardees were collected from reputable organizations including the American Society of Civil Engineers (ASCE), Canadian Society for Civil Engineering (CSCE), American Concrete Institute (ACI), and the Institution of Civil Engineers (ICE). Non-awardee data were adapted from previously published datasets compiled by Raheel et al. and Usman et al. [6, 32]. Table 1 summarizes the dataset characteristics.

Data extraction was performed using the *Publish or Perish*[1] tool, which retrieves bibliometric metadata from Google Scholar using advanced query algorithms. To maintain temporal proportionality, the number of non-awardees was matched to awardees for each award year. For example, if 15 awardees were identified in 1991, 15 non-awardees were selected with similar profiles from prior years.

Prior to analysis, the dataset underwent extensive preprocessing to ensure accuracy and relevance. This included verifying data integrity, eliminating duplicate entries, and filtering for civil engineering content. Author disambiguation techniques were also applied to resolve name inconsistencies and consolidate records, thereby enhancing the dataset's reliability. Two main disambiguation scenarios were handled manually. In the first, different researchers had identical first and last names; in these cases, we distinguished authors based on affiliation, research domain, and co-authorship patterns. In the second scenario, authors with identical last names but different first names required evaluation to determine whether they were variants of the same individual or different people. We verified publication topics, venues,

1 https://harzing.com/resources/publish-or-perish

Table 1 Dataset statistics

Dataset overview	
Total Authors	1,180 (590 Awardees / 590 Non-Awardees)
Total Citations	24,061,210
Total Publications	214,672
Award distribution	
Awardees from ASCE	140
Awardees from CSCE	177
Awardees from ACI	155
Awardees from ICE	118

and timelines to aid this decision. Any entries that remained ambiguous after this process were excluded from the dataset to ensure data integrity. These preprocessing steps were performed using a combination of manual inspection and automated Python scripts. The Publish or Perish tool was used for data extraction, while custom scripts were developed to detect duplicates, handle name variations, and apply domain-specific filters.

3.2 Calculation of author assessment parameters

This section details the computation of 64 author assessment parameters derived from the collected dataset. These parameters are grouped into four distinct categories, each designed to capture different aspects of a researcher's scholarly impact. The categories and their respective parameters are outlined below.

3.2.1 Primitive parameters

Primitive parameters are fundamental bibliometric indicators that describe basic scholarly output and citation behaviors. These include:

- Total Publications
- Total Citations
- Total Years (active publishing span)
- Cites per Year
- Cites per Paper
- Authors per Paper
- Cites per Author
- Papers per Author

3.2.2 Publication and citation count-based parameters

This category encompasses widely used and advanced indices that quantify academic productivity and citation impact. The parameters include:

- H-index, G-index, E-index, H-core Citation, A-index, R-index, P-index, M-index, F-index, T-index

- Q2-index, Tapered H-index, Maxprod, Wu-index, Pi-index, Weighted H-index, H(2)-index, Woeginger-index
- Gh-index, Rm-index, X-index, Hg-index, H2 Upper-index, H2 Center-index, H2 Lower-index
- K Dash-index, Rational H-index, Real H-index, I10-index, Normalized H-index, K-index, W-index, H Dash-index

3.2.3 Author count-based parameters

These indices are designed to normalize credit based on the number of co-authors or collaborations, emphasizing individual contribution. Parameters include:

- HI-index, HI-norm, Hm-index, Gm-index, Hf-index, Gf-index, GF-index
- K-norm index, W-norm index, Pure H-index
- Fractional G-index, Fractional H-index, Normalized HI-index

3.2.4 Age-based parameters

Age-based parameters account for the influence of publication age on citation patterns, helping to normalize for career length. Included indices are:

- Platinum H-index, M-Quotient Index, AW Index, AR Index
- V Index, Ha Index, Hc Index (Contemporary H-index)
- AWCR (Age-Weighted Citation Rate)

All of the above parameters, along with their calculations and descriptions, are presented in Table 3 in the Appendix.

3.3 Ranking of author assessment parameters

In machine learning, feature ranking is a critical step in identifying the most significant attributes for tasks such as dimensionality reduction, improving interpretability, reducing overfitting, optimizing prediction models, and enhancing feature engineering processes [35].

As shown in Fig. 2, a multilayer perceptron (MLP) classifier combined with a recursive feature elimination technique was employed to assess parameter importance. MLPs are flexible and have been effectively applied across classification, prediction, and regression domains [36].

The MLP used is a feed-forward neural network composed of multiple hidden layers [37]. In classification tasks, the number of input layer neurons corresponds to the number of features, and the output layer matches the number of classes. Hidden layers form a fully connected network, trained via backpropagation. Forward propagation is computed using:

$$X = WA + b \tag{1}$$

where X is the output matrix, W the weight matrix, and b the bias vector.

To ensure normalized output, an activation function is applied:

$$C = g(X) \tag{2}$$

We employed the rectified linear unit (ReLU) for hidden layers:

$$f(X) = \max(0, X) \tag{3}$$

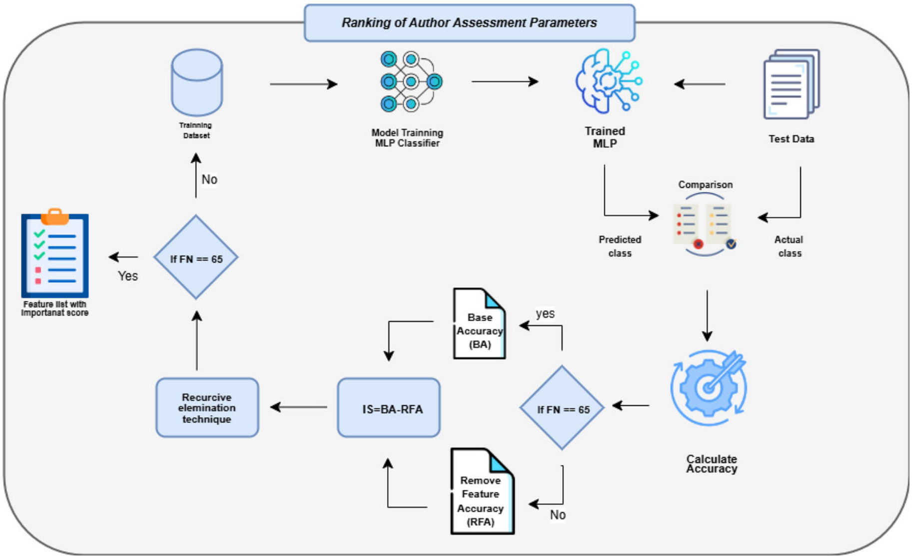

Fig. 2 Feature ranking process: The dataset is split into training and validation sets (80:20). A multilayer perceptron (MLP) is trained on the training set, and baseline accuracy (BA) is computed using all 64 features. In successive iterations, one feature is removed, the model is retrained, and the resulting accuracy (RFA) is recorded. The importance score (IS) is calculated as the difference between BA and RFA. This process continues until all features are evaluated, resulting in a ranked list based on IS

The output layer used the Softmax activation function:

$$\text{Softmax}(X_i) = \frac{e^{X_i}}{\sum_{j=1}^{J} e^{X_j}} \tag{4}$$

where J is the number of output classes.
The model's loss is measured by:

$$L(z, \hat{z}) = \frac{1}{n}\sum_{i=1}^{n}(z_i - \hat{z}_i)^2 \tag{5}$$

To stabilize training, we applied batch normalization:

$$X_i = \frac{X_i - \text{Mean}_i}{\text{Standard Deviation}_i} \tag{6}$$

The model consisted of 10 hidden layers with 10 neurons each, trained using the Adam optimizer (learning rate = 0.0003, batch size = 64, epochs = 100). Early stopping was applied after 40 stagnant epochs. Feature importance was derived via recursive elimination and validated using performance variation [38].

3.4 Prediction using top-ranked parameters

After ranking, the top five features from each parameter category—primitive, citation-based, author-based, and age-based—were selected. These were used to evaluate their influence on identifying awardees among the top 100 researchers. The analysis confirmed the effectiveness of the selected features in highlighting impactful researchers.

3.5 Rule mining using top 5 parameters from each category

Decision trees are widely used in machine learning due to their interpretability and classification accuracy [39, 40]. They work by recursively partitioning the dataset based on selected features until terminal conditions are met—either pure nodes or no gain from further splits.

The node splitting criteria are typically the Gini index or information gain. We selected the Gini index for its performance with numerical data and its resilience in high-cardinality feature spaces [41, 42]. The Gini index is defined as:

$$GI = 1 - \sum_{j=1}^{n} (P_j)^2 \tag{7}$$

where P_j is the probability that a sample belongs to class j. A Gini index of 0 indicates perfect purity; 1 implies maximum impurity.

Due to the high dimensionality of our data, decision trees initially became complex and overfitted. To mitigate this, post-pruning was applied: trees were grown to maximum depth and then pruned by removing subtrees with minimal contribution. The pruning process was guided by a cost–complexity trade-off that penalizes both classification error and subtree size. This resulted in compact, interpretable trees that facilitated extraction of generalizable rules for each parameter category.

4 Results and discussion

This section presents and analyzes the experimental results obtained by applying the proposed methodology to the civil engineering dataset.

4.1 Parameter ranking

To evaluate the influence of individual parameters on model performance, we assessed their average impact scores and corresponding classification accuracies across four categories: primitive, publication age-based, author count-based, and publication/citation-based parameters. The results are illustrated in Figs. 3, 4, 5, 6 and 7.

In the primitive parameters category (Fig. 3), *Cites per Author* showed the highest average impact of 0.22 with an accuracy of 62.19%, followed by *Cites per Year* (impact: 0.21; accuracy: 57.19%). Both *Author per Paper* and *Total Publications* had impacts of 0.20, but lower accuracies at 47.50% and 46.25%, respectively.

In the publication age-based parameters (Fig. 4), the *AW Index* led with an impact of 0.19 and an accuracy of 69.69%. The *M-Quotient Index* and *Platinum H Index* followed with impacts of 0.16 and 0.15, and accuracies of 62.81% and 47.50%, respectively.

Among author count-based parameters (Fig. 5), the *K-Norm Index* exhibited the highest impact of 0.20 and an accuracy of 66.56%, while the *Normalized HI Index* had an impact of 0.19 with 61.88% accuracy. Other strong contributors included the *GF Index*, *HI Index*, and *HM Index*, each with impact scores around 0.18.

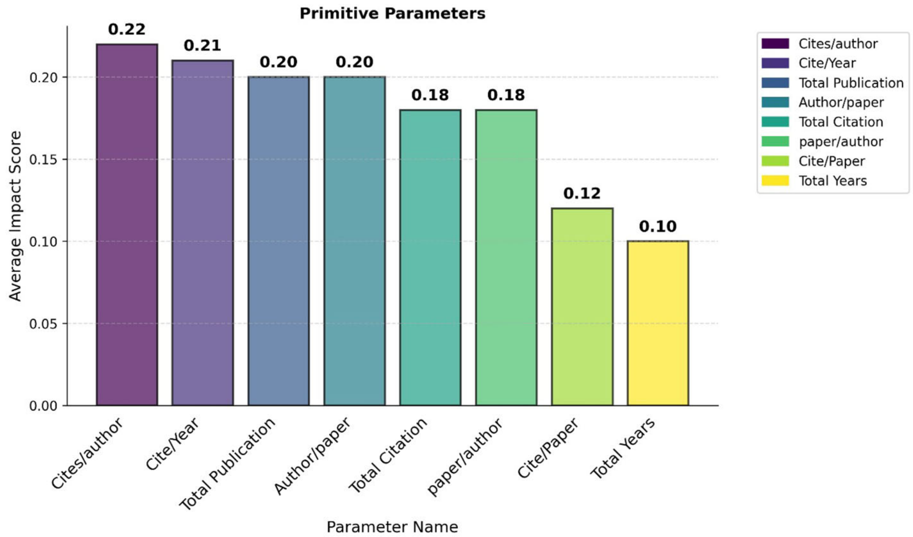

Fig. 3 Primitive parameters

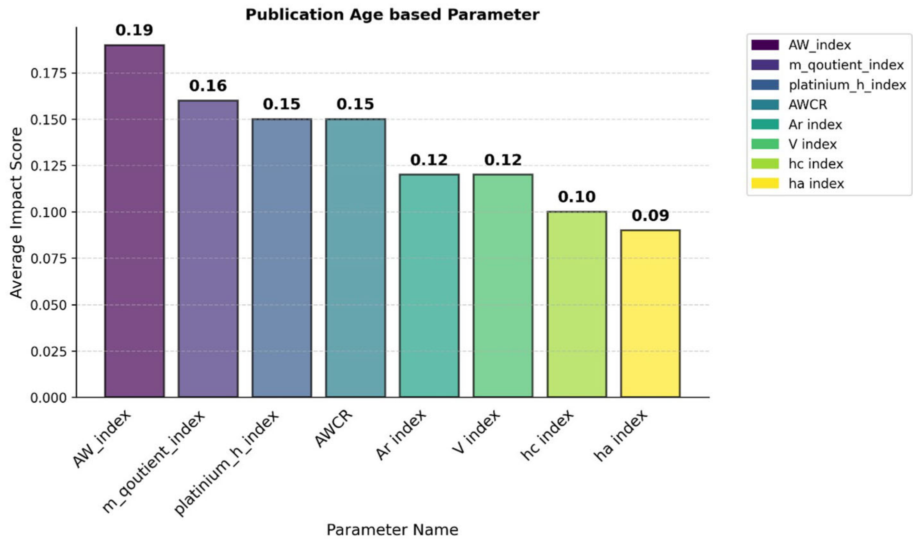

Fig. 4 Publication age-based parameters

In the publication and citation count-based category (Fig. 6), the *T Index* was the most impactful feature, with an average impact of 0.23 and an accuracy of 71.88%. The *I10 Index* followed closely (impact: 0.22; accuracy: 48.44%), while the *Tapered H Index* recorded an impact of 0.21 with a 55.00% accuracy.

Overall (Fig. 7), the most influential features across all categories were the *T Index*, *Cites per Author*, and *I10 Index*, underlining their relevance in predicting academic recognition within the civil engineering domain.

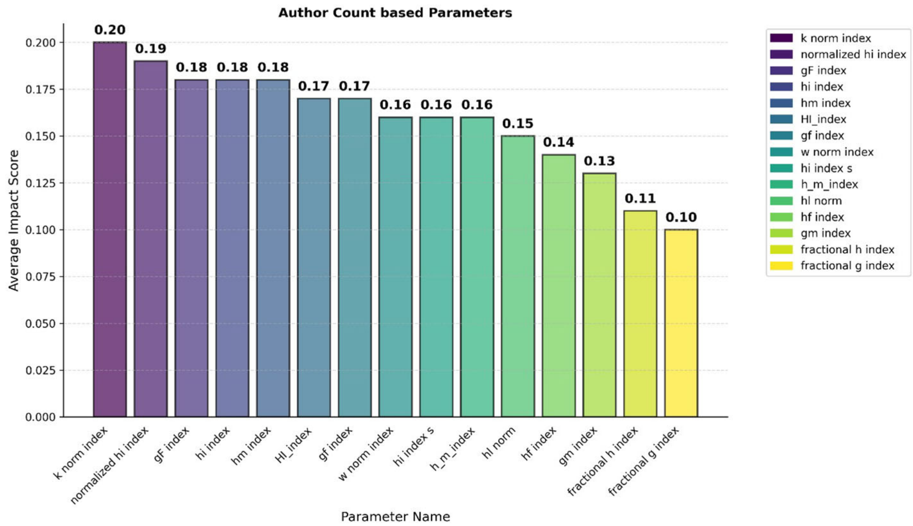

Fig. 5 Author count-based parameters

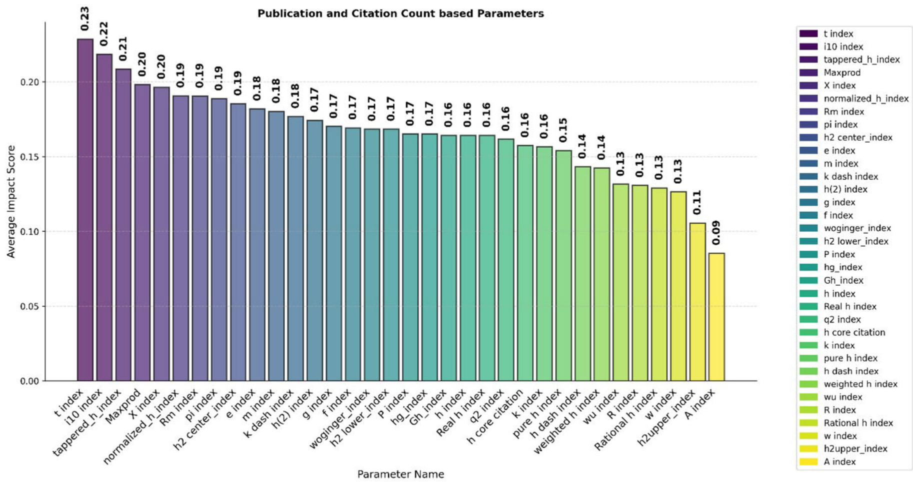

Fig. 6 Publication and citation count-based parameters

4.2 Prediction using top-ranked parameters

Using the top five parameters from each category, we analyzed the award trends among the top 100 ranked researchers. Figure 8 shows that primitive metrics such as *Total Citations*, *Cites per Year*, *Author per Paper*, and *Cites per Author* identified 61%, 51%, 52%, and 38% of awardees, respectively.

In the age-based category (Fig. 9), the *Platinum H Index* and *M-Quotient Index* highlighted 41% and 53% of awardees, while the *AW Index* and *AWCR* accounted for 49% and 53%, respectively.

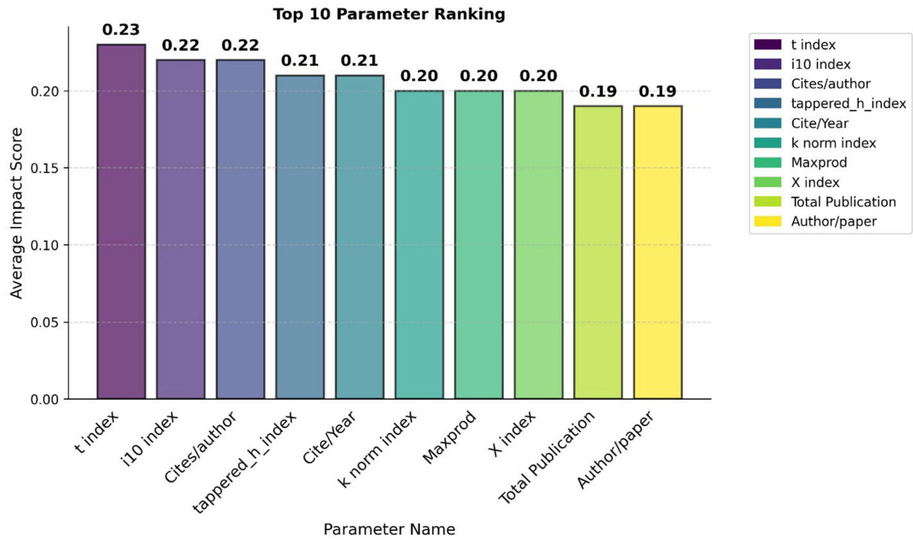

Fig. 7 Combined ranking across all categories

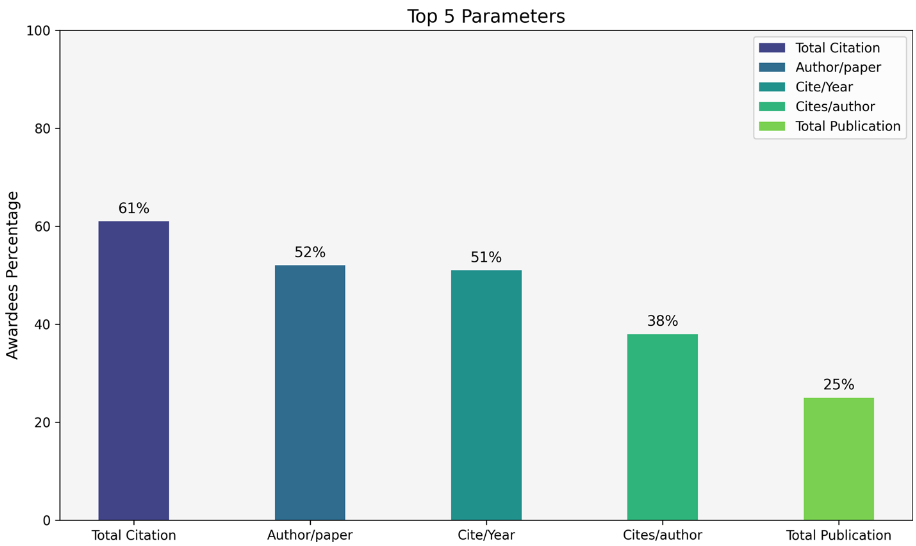

Fig. 8 Awardee identification using top primitive parameters

As illustrated in Fig. 10, author count-based metrics such as *HM Index* and *GF Index* identified 51% and 48% of awardees. The *Normalized H Index*, *K-Norm Index*, and *HI Index* contributed 46%, 48%, and 47%, respectively.

Publication and citation metrics (Fig. 11) such as the *T Index*, *Maxprod*, and *X Index* accounted for 50%, 52%, and 49% of awardees. The *Tapered H Index* and *I10 Index* captured 40% and 41%.

As shown in Fig. 12, when all parameters were combined, *Cites per Year* emerged as the most influential feature, identifying 51% of awardees, followed by *T Index* (50%), *Maxprod*

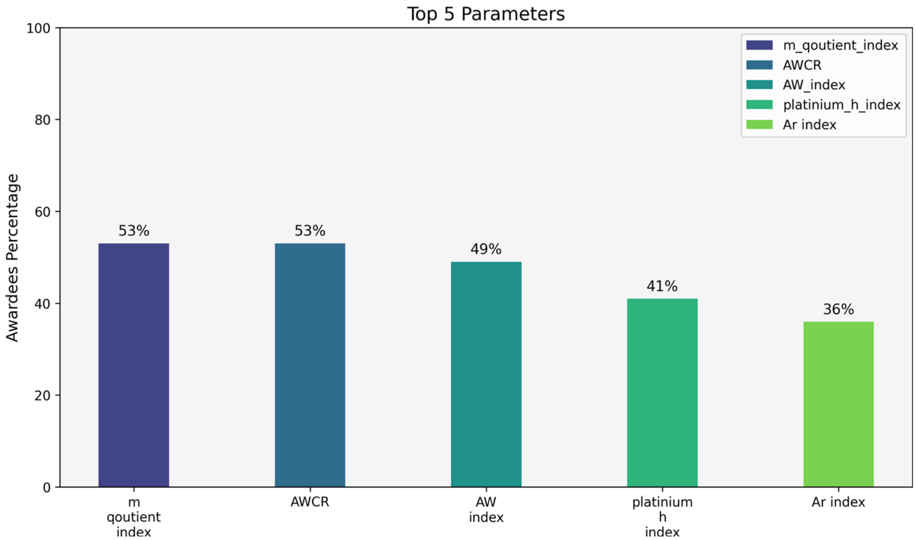

Fig. 9 Awardee identification using age-based parameters

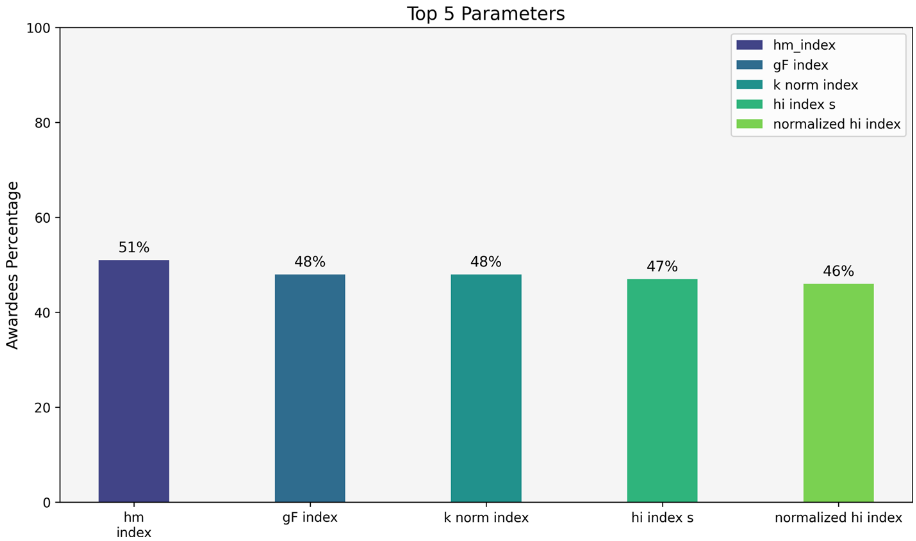

Fig. 10 Awardee identification using author count-based parameters

(52%), and *I10 Index* (41%). These findings indicate that primitive and age-based metrics are particularly effective in distinguishing top researchers.

5 Rule mining

This section presents a set of extracted rules, one from each parameter category, derived from the top five ranked features identified in the previous analysis. To uncover recurring patterns

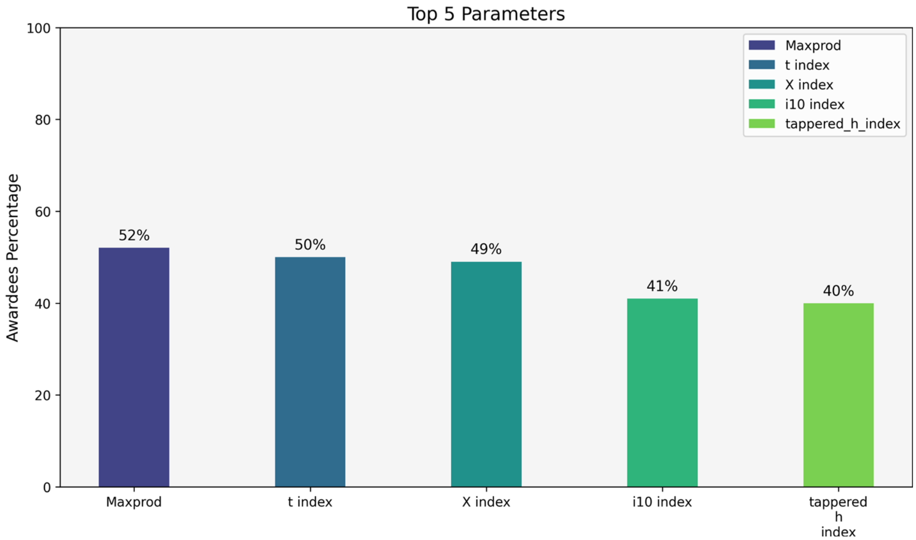

Fig. 11 Awardee identification using publication and citation parameters

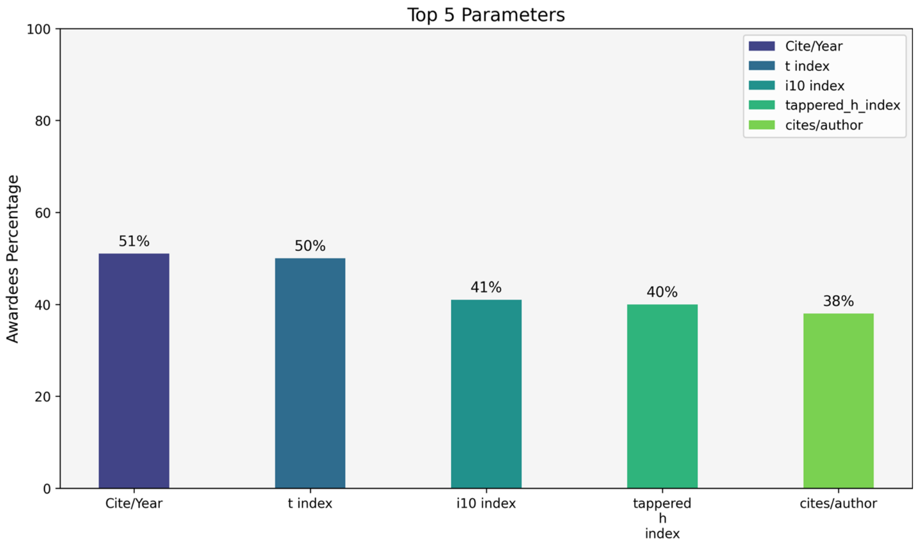

Fig. 12 Awardee identification using top features across all categories

among awardees, we employed a decision tree algorithm using the Gini index as the splitting criterion. For each category, a complete decision tree was constructed, generating multiple decision rules.

Each rule serves as a standalone framework for assessing researchers based on quantifiable attributes. The final nodes (leaf nodes) in the decision tree represent the classification outcomes: blue and light blue nodes indicate rules that lead to the positive class (awardee), whereas other colored nodes correspond to the negative class (non-awardee). These class assignments are determined by the majority of records reaching each node. For example, if a rule applies to 50 records, with 40 being awardees and 10 non-awardees, the rule is classified as identifying awardees.

We extracted all rules that led to the positive class and ranked them based on the number of awardees identified. However, some decision tree rules included conditions that are not practical in real-world evaluations. Typically, the rules take two forms:

1. The parameter value must be less than or equal to a threshold X,
2. The parameter value must be greater than or equal to X.

The first type suggests that exceeding a certain threshold could disqualify a researcher from recognition. This is often unrealistic and contradicts practical academic merit evaluation. Such conditions are a limitation of decision trees, which treat thresholds symmetrically without domain-specific contextualization. Since these metrics represent achievements, applying upper limits as disqualifying thresholds is counterintuitive and may inadvertently discourage excellence.

Therefore, in our real-world interpretation of the rules, we exclude any conditions that impose upper thresholds (i.e., "less than or equal to" constraints) unless they are statistically justifiable or aligned with domain-specific reasoning.

5.1 Rule evaluation metrics

To validate the extracted rules, we use the following performance metrics:

$$\text{Precision} = \frac{\text{Awardees Returned by Rule}}{\text{Total Authors Returned by Rule}} \tag{8}$$

$$\text{Recall} = \frac{\text{Awardees Returned by Rule}}{\text{Total Awardees in Dataset}} \tag{9}$$

$$\text{F-Measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

Based on these metrics, we ranked the extracted rules and identified the top-performing ones across different categories. These rules emphasize critical factors that may be adopted by the broader scientific community to establish objective and interpretable frameworks for academic recognition.

In the subsequent section, we detail the most effective rules extracted from each parameter category, derived from our civil engineering domain dataset.

6 Extracted rules from decision trees

In this section, we present one representative rule from each parameter category, derived from the top five features identified in the previous analysis. These rules were extracted using decision tree models and evaluated for predictive performance using standard classification metrics.

6.1 Rule for primitive parameters

The top five primitive parameters were: *Total Publications*, *Total Citations*, *Cites per Year*, *Cites per Author*, and *Authors per Paper*. These parameters represent basic productivity and citation behaviors. The decision tree constructed for this category achieved 69% accuracy.

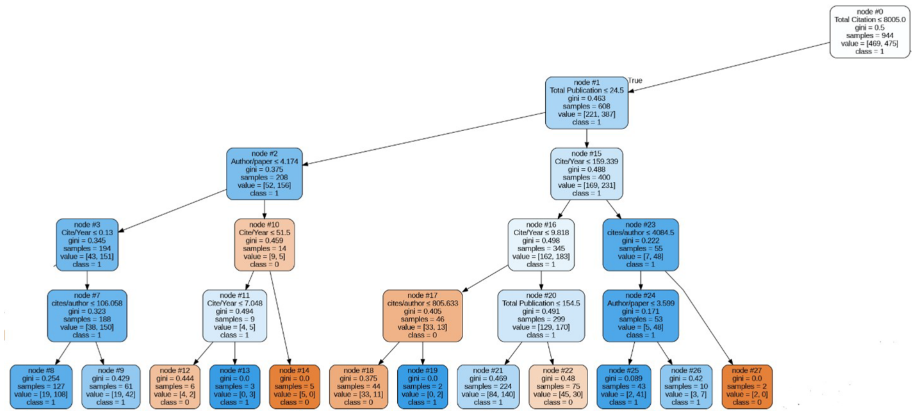

Fig. 13 Decision tree for primitive parameters

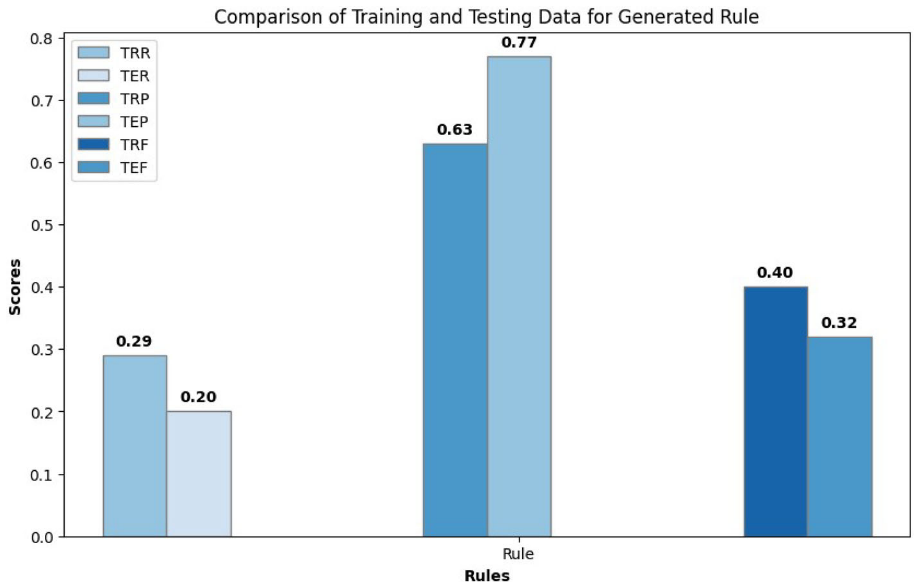

Fig. 14 Performance comparison of rule (primitive parameters)

From 13 extracted rules, the top-performing rule had an F-Measure of 0.40 (Recall: 0.29, Precision: 0.63). The rule is visualized in Fig. 13.

Top Rule: IF *Total Publications* $\leq$ 24.5 AND *Cite/Author* $>$ 106.5 AND *Cite/Year* $>$ 0.13 AND *Author/Paper* $\leq$ 4.174 AND *Total Citations* $\leq$ 8005 $\Rightarrow$ **Award Recipient**

This rule emphasizes the influence of citation efficiency over raw counts. Figure 14 shows the rule's performance on both training and test datasets.

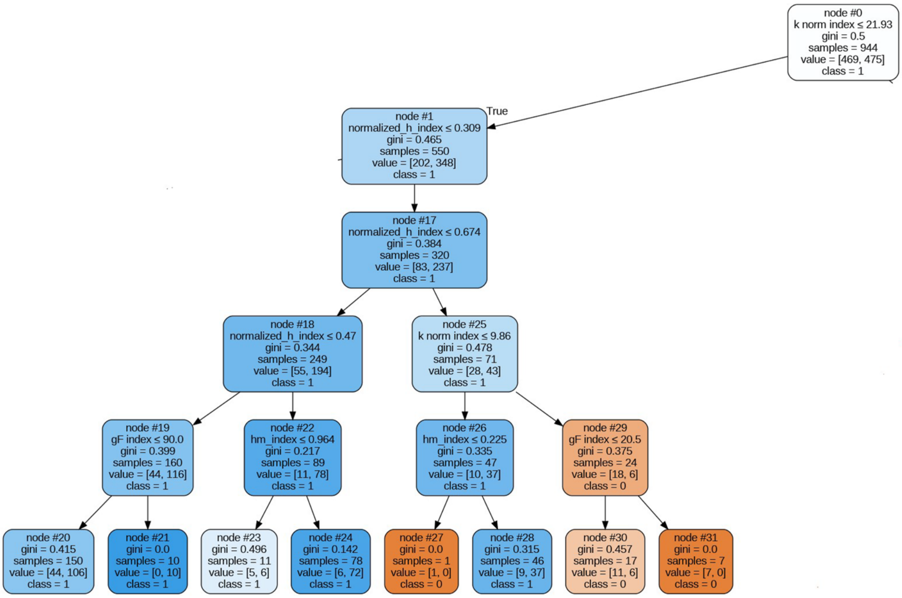

Fig. 15 Decision tree for author count-based parameters

6.2 Rule for author count-based parameters

The top five parameters were: *Normalized H Index*, *GF Index*, *HI Index*, *HM Index*, and *K-Norm Index*. The model yielded 64% accuracy, with the best rule scoring an F-Measure of 0.34 (Recall: 0.22, Precision: 0.71). See Fig. 15.

Top Rule: IF *Normalized H Index* > 0.67 AND *K-Norm Index* ≤ 9.9 AND *HM Index* > 0.23 $\Rightarrow$ **Award Recipient**

6.3 Rule for age-based parameters

The top five were: *Platinum H Index*, *AW Index*, *M-Quotient Index*, *AR Index*, and *AWCR* (Fig. 16). The best rule had a strong F-Measure of 0.49 (Recall: 0.35, Precision: 0.82). See Fig. 17.

Top Rule: IF *AR Index* > 72.24 AND *Platinum H Index* > 40.5 AND *AWCR* > 227.6 $\Rightarrow$ **Award Recipient**

6.4 Rule for publication and citation count-based parameters

The top five parameters included: *T Index*, *Tapered H Index*, *Maxprod*, *X Index*, and *I10 Index* (Fig. 18). The top rule achieved (Fig. 18) an F-Measure of 0.41 (Recall: 0.29, Precision: 0.70). See Fig. 19.

Top Rule: IF *Maxprod* ≤ 2665.5 AND *Tapered H Index* > 6.3 AND *X Index* > 2.1 $\Rightarrow$ **Award Recipient**

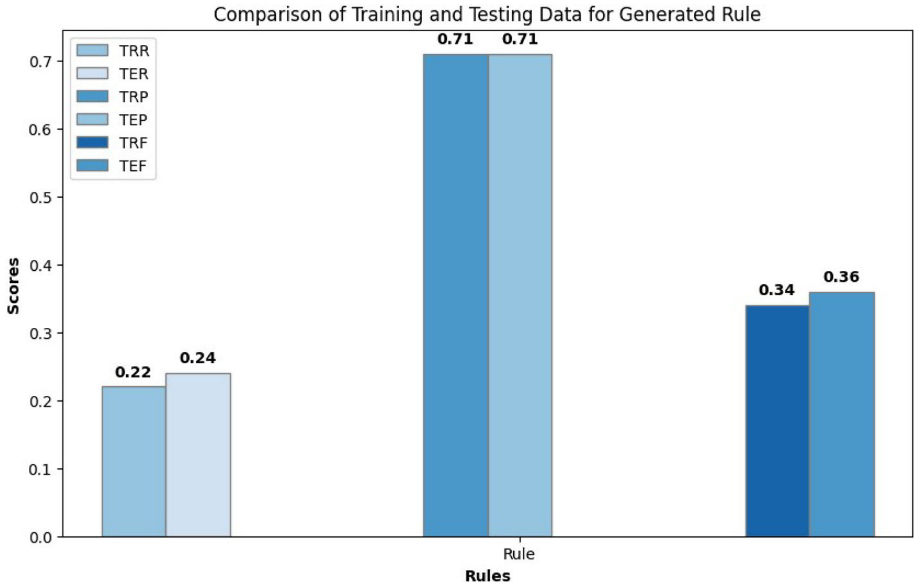

Fig. 16 Performance comparison of rule (author count-based parameters)

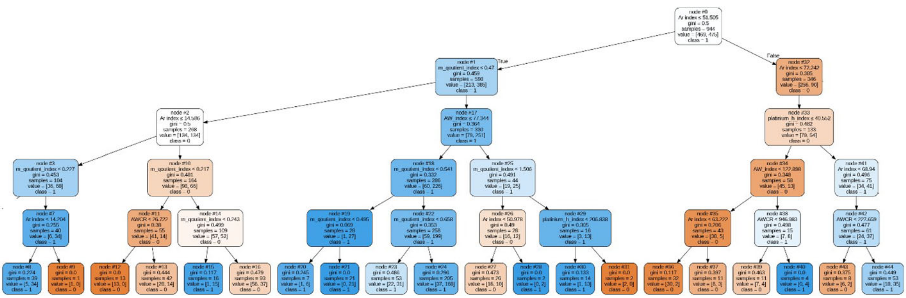

Fig. 17 Decision tree for age-based parameters

6.5 Rule combining all parameter categories

When all categories were combined, the top five features were: *Cite/Year*, *T Index*, *Tapered H Index*, *I10 Index*, and *Cite/Author* (Fig. 20). The final rule achieved an F-Measure of 0.35 (Recall: 0.23, Precision: 0.80). See Fig. 21.
Top Rule: IF *Cite/Author* > 0.625 AND ≤ 115.1 AND *Cite/Year* > 0.13 AND *Tapered H Index* $\leq 6.9 \Rightarrow$ **Award Recipient**

6.6 Comparison of rule-based vs. single-metric thresholds

To evaluate whether combining multiple bibliometric parameters into interpretable decision rules offers tangible performance gains, we conducted a comparative analysis between each rule and its strongest individual parameter. For a fair comparison, we applied the same

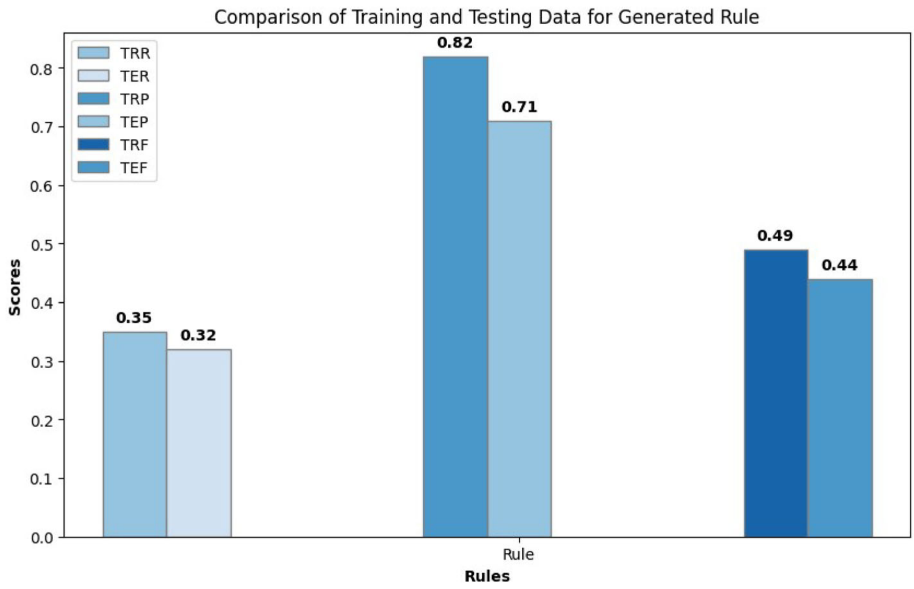

Fig. 18 Performance comparison of rule (age-based parameters)

threshold from the rule to the corresponding single metric and computed performance metrics including Precision, Recall, and F1 score (Fig. 22).

As shown in Table 2, rule-based combinations of bibliometric indicators consistently outperform single-metric thresholds across all performance metrics. In particular, improvements in F1 scores and recall demonstrate that these rules better identify awardees without increasing false positives significantly.

For example, Rule 4 using both the Tapered H Index and X Index—achieved an F1 score of 0.54, compared to only 0.42 when using Tapered H Index alone. Similarly, the three-feature rule in Rule 3 (AR Index, Platinum H Index, and AWCR) shows noticeable gains in both precision and recall over AR Index alone.

These results confirm the advantage of data-driven, interpretable rules in modeling complex academic impact profiles. Such combinations capture the multifaceted criteria often considered by expert panels or award committees and thus provide a more robust and scalable recognition framework.

7 Discussion on generated rules

To complement the empirical findings, this section offers conceptual reasoning behind the predictive power of the most effective parameters used in our rules. In particular, *Cite/Author* and *Tapered H Index* stand out due to their structural alignment with real-world academic recognition.

The *Cite/Author* metric reflects the average citation per contributing author, effectively accounting for author inflation and indicating an individual's intellectual leadership. This becomes particularly important in civil engineering, a field where collaboration is common.

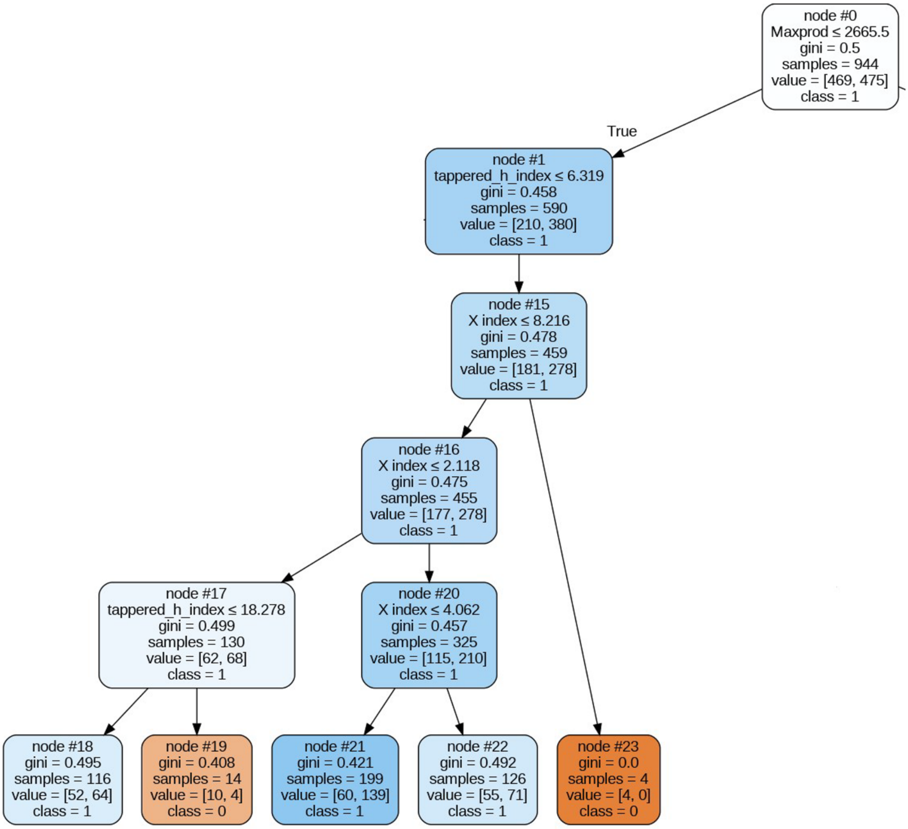

Fig. 19 Decision tree for publication and citation count-based parameters

The *Tapered H Index*, on the other hand, improves on the h-index by giving weighted importance to highly cited papers while still considering moderately cited ones. This allows for a balanced representation of both consistent performance and high-impact contributions—characteristics often valued in award decisions.

While Section 6.6 quantitatively demonstrates that rule-based combinations outperform single-metric thresholds, it is also important to highlight that some parameters—such as *Total Publications*, *Maxprod*, and *K-Norm Index*—were excluded due to being captured by "less than" conditions. These were omitted to maintain interpretability and to avoid discouraging higher productivity.

Beyond classification performance, these interpretable rules offer practical value. For researchers, the rules provide clear thresholds (e.g., *Cite/Author* $>$ 106.5) as performance goals. For institutions, they enable the design of transparent, scalable, and reproducible recognition systems. Unlike black-box models, our framework supports fairness and accountability by making its criteria explicit and aligned with real-world recognition patterns.

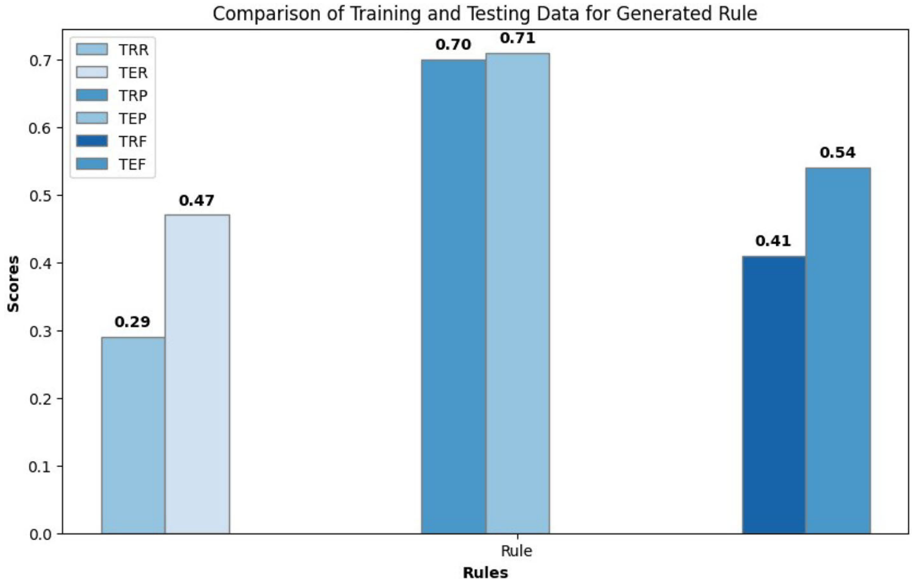

Fig. 20 Performance comparison of rule (publication and citation parameters)

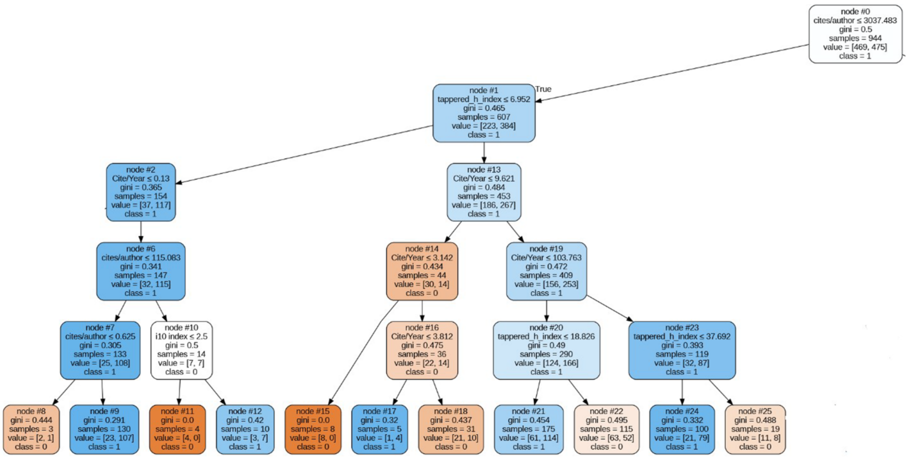

Fig. 21 Decision tree combining all parameter categories

8 Conclusion

Evaluating the scholarly achievements of researchers has become a key area of focus in recent decades. A multitude of bibliometric indices have been proposed to quantify research contributions, yet consensus on the most effective and interpretable parameters remains elusive. This study categorized 64 author assessment parameters into four distinct groups: primitive metrics, author count-based indices, publication and citation count-based indices, and age-based indices. Using a machine learning approach, we ranked these parameters and generated interpretable rules for identifying award-winning researchers in the civil engineering domain.

Fig. 22 Performance comparison of rule (combined parameters)

Table 2 Performance Comparison: Rule-Based vs. Single-Metric Thresholds

Rule	Condition	Precision	Recall	F1 Score
1 (Single)	Cite/Author > 106.5	0.16	0.65	0.26
1 (Rule)	Cite/Author > 106.5 AND Cite/Year > 0.13	0.20	0.77	0.34
2 (Single)	Normalized H Index > 0.67	0.18	0.57	0.27
2 (Rule)	Normalized H Index > 0.67 AND HM Index > 0.23	0.24	0.71	0.36
3 (Single)	AR Index > 72.24	0.25	0.59	0.35
3 (Rule)	AR Index > 72.24 AND Platinum H Index > 40.5 AND AWCR > 227.6	0.32	0.71	0.44
4 (Single)	Tapered H Index > 6.3	0.36	0.51	0.42
4 (Rule)	Tapered H Index > 6.3 AND X Index > 2.1	0.47	0.61	0.54
5 (Single)	Cite/Author > 0.625	0.14	0.60	0.23
5 (Rule)	Cite/Author > 0.625 AND Cite/Year > 0.13 AND Tapered H Index ≤ 6.9	0.18	0.70	0.29

Our findings reveal that *Cites per Author* is a critical factor in the primitive category, while the *K-Norm Index* is the most impactful in author count-based metrics. The *T Index* emerged as a leading indicator within the publication and citation category, and the *AW Index* proved to be highly relevant among age-based parameters. Notably, rules derived from publication and citation count-based parameters yielded the most favorable results, suggesting their superiority in predicting academic impact.

While the rule-based framework enhances the probability of recognition, final decisions remain subject to qualitative judgments and institutional criteria. Nevertheless, the proposed model offers valuable insights for individual researchers aiming to strengthen their academic profiles and for institutions seeking to implement more transparent and objective recognition frameworks.

9 Future work

Several avenues exist for extending this research. First, we plan to evaluate the generalizability of the identified parameters across other disciplines, including medicine, the humanities, and interdisciplinary fields. This cross-domain analysis will help assess the robustness and relevance of the current parameter set.

Second, we aim to develop new indices that more comprehensively capture an author's lifetime scholarly contributions. These may include novel metrics that account for co-author influence, publication longevity, and the impact of collaborative networks—elements that are often overlooked by traditional indices.

Third, future work will explore the use of deep learning architectures to enhance the predictive accuracy and scalability of our framework. Techniques such as graph neural networks and transformers may offer improved modeling of complex relationships among bibliometric variables.

In addition, we are interested in integrating subjective and contextual factors—such as mentorship, funding acquisition, and project leadership—into the evaluation model. For instance, the Q-factor introduced by Sinatra et al. (2016) presents a promising multidimensional framework for assessing researcher influence beyond citations alone.

Finally, we will address several broader questions: Can integrated quantitative metrics significantly advance the field of scientometrics? Are these metrics feasible for deployment in academic search engines and digital libraries? And, is there a need for new indices that better support subjective and peer-review-based recognition systems?

Collectively, these future directions aim to enhance the fairness, interpretability, and domain relevance of academic performance assessment frameworks.

Appendix A

See Table 3.

Table 3 Indices calculation Formulas

Name of Index	Calculation
Total Publication	Total No. of Publications of a researcher
Total Citation	Total No. of Citations of a researchers
Total Years	Total number of years since the researchers first publication
Cites / Year	Total citations count / Total number of years since first paper
Cites / Paper	Total citations/total papers
Author / Paper	Calculate the sum of authors contributing to the publications associated with the specified author, then divide this total by the number of papers
Cites / author	Compute the citations per publication by dividing the citations for each paper by the number of authors, and then sum these adjusted citation values. This sum represents the single-authored equivalent number of citations for the specified author
Papers / author	Calculate the single-authored equivalent number of papers for the specified author by dividing each publication by the number of authors and summing the fractional author counts
H-index	h = max (numbers of publication with >= h citations count)
G-index	A collection of papers is assigned a g-index, denoted as 'g,' where 'g' is the highest rank for which the top g papers collectively amass at least g^2 citations
Hg-index	$hg - index = \sqrt{h * g}$
	Where h represents h-index and g represents g-index
A-index	$A - index = \frac{1}{h} \sum_{p=1}^{h} cit_p$
	Where A is the A-index of the scholar, h represents the h-index and cit_p is the citation count of the p^{th} article
R-index	$R - index = \sqrt{\sum_{p=1}^{h} Cit_p}$
	Where h represents the h-index and cit_p is the citation count of the p^{th} article
P-index	$P - index = (\frac{C^2}{p})^{\frac{1}{3}}$
	The p-index strikes the best balance between total number of citations (C) and the mean citation rate (C/P)
Q^2-index	$Q^2 = \sqrt{h * m}$
	Where h represents h-index and m represents m-index
K-index	$K - index = \frac{\frac{C}{P}}{\frac{C(h-tail)}{C(h-core)}}$
	Where C represents total citation, p represents of p^{th} article, h-tail represents h-tail article citation and h-core represents h-core citation
E-index	$e - index = \sum_{p=1}^{h} Cit_p - h^2$
	Where Cit_p represents citation of p^{th} article and h represents h-index
f-index	$f - index = \binom{max}{f} \frac{1}{\frac{1}{f} \sum_{p=1}^{f} \frac{1}{Cit_p}} \geq f$
	Where cit_p is the citation count of p^{th} article. The f-index never goes beyond the total number of publications
T-index	$T - index = \binom{max}{t} exp\left[\frac{1}{t} \sum_{k=1}^{t} ln(Cit_k)\right] \geq t$
	Where cit_k is the citation count of k^{th} article

Table 3 continued

Name of Index	Calculation
Tapered h-index [?]	$H_{T(j)} = \begin{cases} \frac{n_j}{2j-1}, & n_j \leq j \\ h_{T(j)} = \frac{j}{2j-1} + \sum_{i=j+1}^{n_j} \frac{1}{2j-1}, & n_j > j \end{cases}$
Wu Index	The w-index of an author is determined by calculating it as follows: if at least w of their articles have accumulated 10w citations each, while the remaining publications have garnered fewer than 10(w+1) citations each
Weighted h-index	$R_w(k) = \frac{\sum_{p=1}^{k} \mathrm{Cit}_p}{h}$ Where h is the h-index and Cit_p is the citation count of the p^{th} article. Then, the weighted h-index is defined as follows $h_w = \sqrt{\sum_{k=1}^{R} \mathrm{Cit}_k}$ Where Cit_k is the citation count of the k^{th} article and R is the largest rank among all publications such that the k^{th} weighted rank $\leq \mathrm{Cit}_k$
h(2)-index	The h(2)-index is defined as the highest integer 'h(2)' for which the scholar's top h(2) most cited articles each have received at least $(h(2))^2$ citations
Woeginger Index	$w = \binom{max}{w}(Cit_p \geq w - p + 1) \quad for\ all \quad p \leq w$ where $cit_p$is the citation count of p^{th} article and w is the maximum number of publications
Rm-index	$R_m = \sqrt{\sum_{k=1}^{h} \mathrm{Cit}_k^{\frac{1}{2}}}$ Where cit_k is the citation count of k^{th} article
m-index	The m-index is computed as the median number of citations received by the h-core articles
X-index	$x = \sqrt{\binom{max}{k} kCit_k}$ Where cit_k is the citation count of k^{th} article
h2 upper-index	$h^2 upper = \frac{\sum_{k=1}^{h}(Cit_k - h)}{\sum_{k=1}^{m} Cit_k} * 100 = \frac{e^2}{\sum_{k=1}^{m} Cit_k} * 100$ Where h is the h-index, cit_k is the citation count of the k^{th} article, $e^2$is the excess citation and m is the total number of articles
h2 center-index	$h^2 center = \frac{h*h}{\sum_{k=1}^{m} Cit_k} * 100$ Where h is the h-index and cit_k is the citation count of the k^{th} article
h2 lower-index	$h^2 lower = \frac{\sum_{k=h+1}^{m}(Cit_k - h)}{\sum_{k=1}^{m}(Cit_k)} * 100$ Where h is the h-index and cit_k is the citation count of the k^{th} article
h̀ –index (h dash)	$h' = Rh = \frac{eh}{t}$ where R represents the head–tail ratio of e and t-index
Rational h-index	$h_{rat} = h + 1 - \frac{k}{2h+1}$ Where h is the h-index and k is the number of citations required to reach h+1 h-index value
I10 Index	This is a straightforward and direct indexing measure that entails counting the total number of papers published by a journal, each of which has received at least 10 citations
Normalized h-index	$normalized\ h - index = \frac{h}{pub_{count}}$

Table 3 continued

Name of Index	Calculation
	Where h represents h-index and pubcount represents total publication
Π *index*	$\Pi\ index = 0.01C(P\Pi)$
	The $\Pi - index$ is equal to the 100th of the number of citations, $C(P\pi)$ to the top square root $(P\pi)$ of the total papers(P)
Gh-index	$Gh^a = \sum_{p=1}^{m} sing(Cit(\text{pub}_b^a) - GH) \quad where\ \ sing(x) = 1, x \geq 0\ and\ \ 0, x \leq 0$
	Where 'm' represents the total number of publications by scholar A, and GH is the h-index of the scholar. This index is also challenging to compute compared to the h-index
W Index	The w-index is defined by the parameter 'w,' signifying the number of a scholar's top articles that have accrued at least 10w citations each. While the w-index can be a valuable measure for gauging the impact of a scholar, it may impose a penalty on young scholars who have recently commenced their work or those who have not yet published a sufficient number of papers
Maxprod	The maximum value of i * c_i can be determined by analyzing the publication rank of an author, where c_i represents the number of citations for the i^{th} most frequently cited paper among all the citations
H-core citation	The h-core citation index considers only publications that have been cited at least h times, disregarding those that have not reached this threshold
K dash index	$k' = \frac{Cit_{all} - Pub_{Count}}{Cit_T - Cit_H}$
	Where cit_{all} represents total citation, pub_{count} represents total publication, cit_t represents total citation of h-tail article and cit_h represents total citation of h-core article
M-Quotient	$M - Quotient = \frac{h-index}{y}$
	Where y represents no. of years the first publication
Hc Index	hc-index $= \alpha \cdot \frac{C(i)}{Y(\text{now}) - Y(i) + 1}$
	Where $Y(\text{now})$ represents the current year, $Y(i)$ represents the publication year, and $C(i)$ represents the citation count of paper i
	hc-index $= \frac{C(i)}{1}, \frac{C(i)}{2}, \frac{C(i)}{3}, \ldots, \frac{C(i)}{n}$
Aw-index	Aw-index $= \sqrt{\sum_{j=1}^{h} \frac{\text{Cit}_j}{a_j}}$
	Where Cit_j represents the citation count of the j-th article, and a_j represents the j-th article out of m total articles
Ar Index	$Ar - index = \sqrt{\sum_{j=1}^{h} \frac{Cit_j}{a_j}}$
	Where Cit_j is the citation of the article and a_j represents a^{th} article, h represents total h-core article
AWCR	This parameter adjusts the citation count based on the length of time that has passed since each publication
v-index	$V = \frac{h}{P(y_{this} - y_o)}$
	Where h is the h-index, y_{this} is the current year and y_0 is the year of first publication

Table 3 continued

Name of Index	Calculation
Platinum H-index	$Platinum - h = \frac{H}{CL} * \frac{cit_{all}}{Pub_{count}}$ Where H is the h-index, CL is the career length, Cit_{all} is the total citation count and pub_{count} is the publication count
Ha Index	The ha-index within a dataset is the highest count of papers in the dataset that have garnered at least ha citations per year on average
HI Index	$h_i = \frac{h}{Avg_a}$ where h represents h-index and Avg_a represents average no. of authors in article
hf Index	$\frac{Yh_f}{\phi(Yh_f)} \geq h_f$ where Y(i) represents citation count and $\phi(i)$ represents average no. of authors in article
gf Index	$gf = \sum_{i=1}^{gf} \frac{Y_i}{\phi_i} \geq g^2 f$ where Y(i) represents citation count and $\phi(i)$ represents average no. of authors in article
gF Index	$gF = (\sum_{i=1}^{k} \frac{1}{\phi(i)})^2 \leq \sum_{i=1}^{k} y_i$ where Y(i) represents citation count and $\phi(i)$ represents average no. of authors in article
Normalized HI Index	normalized hi-index $= \frac{h}{pub_{count}}$ Where h represents the h-index and pub_{count} is the total number of articles
HM Index	$r_{eff}(r) = \sum_{r'=1}^{r} \frac{1}{a(r')} thenc(r(h_m)) \geq h_m \geq c(r(h_m) + 1)$
k-norm index	$k - norm = h - norm + (1 - (h - \frac{norm^2}{\sum_{j=1}^{h-norm} citnorm_i})), \quad \vee h - norm > 1 \; and \; k - norm = 0, \; if \; h - norm = 0$
w-norm index	$w - norm = h - norm + (1 - (h - \frac{norm^2}{totalcit - norm})), \quad \vee h - norm > 0 \; and \; w - norm = \frac{totalcit - norm}{1 + totalcit - norm}, \; if \; h - norm = 0$
gm index	$C_{eff}(g_m) \; where \; C_{eff}(r_{eff}) \quad and \; S_{eff)}(r_{eff}) = \sum_{\acute{r}=1}^{r(r_{eff})} \frac{1}{a(\acute{r})} c(\acute{r})$
pure h index	$h_p(A) = \frac{h}{\sqrt{E(author)}}$ Where h represents h-index and E average no. of authors
fractional h-index	$h_f = max(k \leq \frac{cit(k)}{author(k)})$ Where Cit_k represents citation of article and author(K) represents no. of author in a specific article
fractional g-index	$g_f = max(\sum_{k=1}^{p} \frac{cit_k}{Author(k)} \geq p^2)$
hi norm index	The hl-norm is a modified version of the h-index that normalizes citations, taking into account the number of authors per paper
Real h index	$h_r = \frac{(h+1)cit_h - h.cit_h + 1}{1 - cit_{h+1} + cit_h}$ Where h is the h-index and cit_h is the citation count of the h^{th} article

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Data Availability No datasets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors declare no conflict of interest.

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