Journal of Engineering Education Transformations ,
Volume 38 , No.1 , July 2024 , ISSN 2349-2473, eISSN 2394-1707

10.16920/jeet/2024/v38i1/24171

D-Impact of the Various Strategies on the Author's Impact Score

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Abstract : Classic feature of any research analytics system is to be able to provide a metric based on the given research data given like the citation count and other kinds of data it is important to analyze the given data and give feedback and understand performance of a given research department, Scholar or the research, So we used a novel approach to rate given person based on the research work and comparing it with different works published in the same area, it is to be noted that the score/rating only focuses on the domain rather than rating the whole scholars work this way we can estimate the scholar's performance with respect to one domain which several other types of ratings fail to do so. This method will act advantageously especially in research organizations where appraisals and giving research grants are usually done based on scholar's previous work in a specific domain. We were able to formulate results for 62 different authors from 8 different domains, these domains and authors were picked randomly so as to efficiently understand the working of the methodology we followed four essential steps in this approach namely gathering dataset, applying Glicko-2 ranking algorithm, finding average rating value for all works finally calculating d-impact score using GPA method on the scale of 9. We can conclude that the result is a both domain-specific and more accurate representation of the author's impact. In work we gave introduction regarding methodology and description of existing technologies in section 1, In section-2 we described the need of the proposed methodology with few sample results in existing methodology and proposed one, In section-4 we described the methodology in step by step manner and also presented proposed algorithm with all the required formulae, In section-5 we presented analysis and actual summary of the results, In section-6 we presented the conclusion.

Keywords : Author impact, D-impact score, Elo rating, Glicko-2, Research analytics.

I. Introduction

Measuring the quality of a researcher's work has always been a critical factor in determining the quality of research an educational institute or a research institute has. The conventional method of finding outperforming a researcher by using h-index Hirsch (2005), and i10-index presents its own set of challenges like its inability to estimate the researcher's performance in the long term, or unable to calculate researcher's performance in a specific domain which becomes important for several factors like releasing

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researcher's grant or during appraisals and another such tasks where you need to measure the researcher's capability in the field he is working, one more problem is to understand how institutions are performing in terms of research when compared to other institutes in a specific domain, for example, if you wish to understand how an institution is performing regarding a specific domain like analytical chemistry you only get works published and their citation count or researcher's profile which can't be relied upon because researcher's work is in multiple domains so using h-index, i10-index cannot solve this problem.

The only way we can solve this problem is by having a domain-specific score assigned to every researcher which considers all the works or research material which the researcher could publish and compare them to all the works present in that domain and assign a score which is easier to interpret and also considers. All the different parameters needed to rank that researcher, which is the reason we came up with this specific score called d-impact factor which addresses all the above problems mentioned above and considers all the above ranking parameters are met to give an effective and easy to interpret score to the researcher. For this method we came up with three different steps to calculate the d-impact factor for every researcher which includes collecting the dataset where we take a specific domain and take sampled data set off all the citation count of these works and also collect specific researchers works from this field and then classify the dataset into three parts: low, medium, high and compare this with a researcher's citation values in that domain and come up with an aggregate score. We initially rate all the individual performances, in this case, the citation count of every work published by the person and match up against all works present in that domain, winning against low works might fetch a lesser score than winning against a high-grade work or medium ones the works are rated in accordance to their performance with respect all the different categories once all the works are rated then we calculate an average rating value of all works. For comparison and ranking works we use Glicko-2 ranking algorithm which is a popular ranking algorithm used in many online games, sports etc., This algorithm is specifically used because it also considers parameters like rating deviation and rating volatility which will be usefully in ratings which involve individual performances over time because it considers several other factors like consistency in performance, confidence of rating, etc.

Glickman (2022) provides a rating of players using the Glicko-2 system. The rating parameters are r (rating) RD (rating deviation) σ (rating volatility). The degree of expected fluctuation of the player rating is measured using volatility. Further details about the algorithm are provided in the methodology.

The Elo rating system is used in order to compare adaptive educational systems. Usually, Elo is used for rating the chess players later it exceeds to rate players from different games. Here using Elo system author provides skill of the student and the difficulty of the items (Pelanek, 2016). The Null Hypothesis Significance Testing (NHST) which is usually used for comparing evolutionary algorithms. It is used for checking the performance of one algorithm over various algorithms. Here evolutionary algorithm is assumed as chess players and the objective function of the algorithm is assumed as an outcome of the game (Veček et al., 2014). Goodspeed (2017) compared two parameters Win Ratio and Q Score based on Elo score and analyzed them based on these parameters. For comparing parameters, the author used pairwise comparison technic. Here author used pairwise comparison technic to evaluate the demographics for the online preference surveys.

Lehman & Wohlrabe (2017) used the Elo rating system to rank chess and other disciplines sports players and scientific journals. The key feature of the Elo rating system is an explicit consideration of the factor time and maintain the history of the journal ranking performance. The Elo rating system is used in order to provide adaptive educational systems. Usually, Elo is used for rating the chess players later on it exceeds to rate players from different games. Here using Elo system author provides skill of the student and the difficulty of the items. The Glicko system is used to compare playing strength between chess players and other disciplines players. Here Glicko system ranks the player based on the reliability of the players. This Glicko system has been used by many internet gaming organizations (Glickman, 2011).

Hacker and Ahn (2016) employed eliciting user preference which uses large datasets and generates ranks based on the preferences. This work proposed a new method for eliciting user preference that doesn't depend on user preferences. This method provides interactive gaming between the users and compares the several algorithms to provide pairwise judgment. A new Bayesian skill rating system which is the generalization of the Elo system which is usually used in the rating the chess players. This system has the ability to track the uncertainty of the player. Using inference approximation messages will be generated (Ralf et al., 2006). Jiménez Diaz et al., (2011) developed a method for understanding the player's skill ranking system. For developing a few research experiments will be done. The author provides modifications for the modern rating system which tries to display only inferior performance only. Improvement for Glicko rating system was proposed without affecting the functionality of the Glicko mechanism. Menke et al., (2007) provides an individual rating method for online computer gaming players. In this method, the author tracks the game progress of the player and compares his gameplay with other players and collects large dataset of active online gamers which helps gaming companies to develop games based on the players interested and led the company to profitability.

The Bayesian rating system which is developed in Microsoft research generates probabilistic models for the participants. It will gather the skills of the participants from the different teams and compare the predictive power of the players based on different problems (Nikolenko & Sirotkin, 2010). Silva et al., (2013) uses social network powered research analytics platform for project selection, the author proposes scholarmate.com a research social network platform to build research platforms for project allocation.

Qin et al., (2019) discusses advantages of using machine learning algorithms in data analytics, they also discuss history and evolution of machine learning in the field of data analytics, he gives three possible applications of machine learning in the field of data analytics.

Kudelka et al., (2016) proposes a new methodology to measure author impact using h-index and citation count implements the above methodology and provides experimental results as output. Jia and Qu (2016) propose a new methodology to improve link prediction in citation network using h-index, discuss various other technologies like graph mining and provides analysis of such methodologies. Wang and Li (2017) use h-index on 5-year citation window. In, we observe that various journals are ranked using h-index on 5-year citation window period also provides experimental results as output for analysis. Gao and Nie (2010) propose an improvement in the existing methodology of using h-index and briefly discusses the disadvantages of using the existing methodology and also proposed that it can be used to research missing valuable information.

Dong et al., (2016) proposes a technique on how to predict h-index and several factors contributing to successful author profile building, build a model to predict the impact the author can create. Egghe (2006) proposes a new methodology to rate author's profile g-index which uses a number of citations the author gets for each work and decides score accordingly. CR Cervi et al. (2013) propose a new methodology to rate an Author. It uses spearman's rank coefficient to rate profiles of 404 different research profiles. Aitouche et al. (2018) compares and rates different Scopus journals linked to the field of knowledge management. He (2009) discusses a methodology to solve the selection process in peer-reviewed journals. Maryglod et al. (2018) discuss a methodology of using data mining in sciento metrics for analyzing academic publications. Puiu et al., (2016) proposed a novel approach called city pulse which performs large scale data analytics framework for smart cities.

Zhang et al., (2018) proposed a new approach which incorporates the use of big data analytics for managing production systems more efficiently. Vatrapu et al (2016) proposed a set theory approach to big data analytics to make analytics more efficient. Rind et al., (2013) proposed time bench as a new approach for visual data analytics. Turkay et al., (2016) proposed a new approach for high dimensional data analytics. Jabbar et al., (2018) proposed a new approach called data fusion for localized big data analytics. Huag et al., (2017) proposed a new schema theory-based approach for gene engineering in big data analytics.

Lepinioti et al., (2020) presented a study of prescriptive analytics. Liang & Liu, (2018) proposed a study of different analytics technologies and their applications in the field of business analytics. Seng & Ang, (2017) proposed a new methodology sc-lda for decision making analytics. In the context of assessing the impact of strategies on an author's impact score, a typical approach involves several steps:

Define the Impact Score: Clearly define what the impact score represents. Is it a measure of a researcher's citation count, h-index, publication in high-impact journals, or some other metric? This step is crucial to ensure that the impact score is well-defined and meaningful.

Identify Strategies: Identify the various strategies or factors that could potentially impact the author's impact score. These strategies could include publishing in certain journals, collaborating with influential researchers, promoting research through various channels, participating in conferences, and more.

Data Collection: Gather data on the author's publications, citations, collaborations, and other relevant information. This could involve accessing databases like Web of Science, Scopus, Google Scholar, or other relevant sources.

Pre-Intervention Analysis: Before implementing any strategies, conduct an analysis of the author's current impact score and related metrics. This serves as a baseline against which the impact of the strategies will be measured.

Strategy Implementation: Implement the chosen strategies. This could involve publishing in specific journals, increasing collaboration, presenting at conferences, or engaging with the public to increase visibility.

Post-Intervention Analysis: After a sufficient time has passed for the strategies to take effect, analyze the author's impact score again along with any other relevant metrics. Compare these post-intervention metrics with the baseline metrics to determine the impact of the strategies.

Statistical Analysis: Use appropriate statistical methods to determine if the changes in the impact score are statistically significant. This could involve t-tests, regression analysis, or other relevant techniques.

Qualitative Analysis: Consider qualitative factors that might influence the impact score, such as the quality and significance of the research itself, the author's reputation in the field, and the broader impact of their work beyond traditional metrics.

Iteration and Adjustment: Depending on the results, you might need to iterate and adjust your strategies. Some strategies might have a more significant impact than others, and it's important to refine your approach based on the outcomes.

Documentation: Clearly document the entire process, including the strategies implemented, data collected, analysis methods used, and results obtained. This documentation ensures transparency and reproducibility.

Remember that assessing impact is a complex process, and there might not be a one-size-fits-all approach.

2. Current Methodologies Used

Present technologies present in research analytics generally tend to focus on the amount of impact a works has created in the particular domain it is done by calculating the citation count of each work, or there are technologies which help us to understand scholar's contribution to whole research community or the capability of the scholar this is done by calculating h-index Hirsch (2005), i10-index, G-index.

A. H-index

It is an author level metric which is used to measure the productivity of researchers based on the most cited research works and a number of citations in other research publications.

B. I10-index

It is an author level metric which is used to measure the productivity of the researcher by calculating the number of publications with at least 10 citations of author/Scholar.

C. G-Index

It is author level metric which is used to measure the productivity of researcher by ranking the articles based on their citations in descending order and giving rating top g articles with at least g^2 number of citations (Egghe, 2006).

The following Table 1 gives an analysis and comparison of existing rating techniques it also provides advantages and disadvantages by using such techniques.

The methodology for D-Impact involves defining the purpose and key components, identifying relevant domains through literature review and expert consultation, and selecting quantifiable metrics. Strategies influencing an author's impact, such as collaboration and knowledge dissemination, are outlined, with their impact quantified in each domain. Weights are assigned based on perceived importance, considering temporal factors. Validation is achieved through case studies, ensuring a comprehensive and robust approach to assessing an author's impact across diverse domains.

A comprehensive comparison of the Glicko-2 ranking algorithm with alternative ranking methods involves evaluating key aspects such as accuracy, sensitivity to player performance, computational efficiency, and adaptability to different domains. Glicko-2, known for its Bayesian approach and ability to handle dynamic player ratings, may be compared against other ranking algorithms, such as Elo or TrueSkill. Accuracy in predicting outcomes, especially in diverse scenarios, is a critical factor for evaluation. Sensitivity to player performance variations and the algorithm's responsiveness to changes in skill levels are crucial considerations. Computational efficiency is essential, especially in large-scale systems, to ensure real-time or near-real-time updates. Adaptability to different contexts, including team-based competitions or varied game structures, is another key factor in the comparison. Additionally, the ease of implementation and the algorithm's capacity to handle large datasets efficiently contribute to its practicality in different applications. To conduct a comprehensive comparison, one can employ statistical measures, simulation studies, and empirical analyses using historical data from various domains. The goal is to provide insights into the strengths and limitations of each algorithm under different conditions, facilitating informed decisions on their suitability for specific ranking scenarios.

The step-by-step explanation of the GPA method for calculating the d-impact score involves a systematic approach that enhances clarity and demonstrates the effectiveness of the proposed approach. Initially, the GPA method defines the key components and objectives of the d-impact score, providing a clear foundation for its application. The method then identifies relevant domains through a comprehensive literature review and expert consultation, aligning with the author's field of work. Quantifiable metrics are selected to measure impact within each domain, ensuring a data-driven and objective assessment. Next, the GPA method outlines specific strategies influencing the author's impact, such as collaboration, knowledge dissemination, or engagement with stakeholders. These strategies are quantified within each domain, considering factors like increased visibility or collaborative projects. The method carefully assigns weights to these strategies based on their perceived importance or effectiveness, acknowledging that not all strategies may have equal impact. To substantiate the effectiveness of the proposed GPA method, a direct comparison is made with existing metrics. This involves empirical assessments using diverse datasets to evaluate the accuracy, adaptability, and overall performance of the GPA method in predicting outcomes and accommodating changes in author impact over time. The comparison extends to computational efficiency and ease of implementation, ensuring that the proposed GPA method stands out as a viable and advantageous approach for calculating the d-impact score.

3. Problem Definition

Calculating the impact is essential for any research institution to be its private research firm or any educational institution's impact rating of one's research is crucial in determining several things like research grants, appraisals etc. Hence a score which is both simple and accurate is essential. Conventional techniques like h-index are trivial and sometimes hard to understand and are also not an accurate interpretation of the amount of impact created by the scholar in a domain which is where our scoring comes into place. The D-impact score is not only simple to understand but is also adaptive, efficient and domain-specific. The advantage of using D-impact score can be illustrated by using a simple example, let us consider profile of scholar x in the field of artificial intelligence the scholar has published 5 works with citations as 5,10,15,2,3 and in the field of compilers published 3 works with citations as 4,6,7 traditional impact score do not consider these as different domains which pose many challenges and also these ratings are complex which makes it difficult to understand sometimes the ratings are easy to understand but aren't efficient in representing the research work. Nevertheless, it is important that ratings are specific to the domain and both easy to understand and accurate in representation which is where D-impact score comes into the picture as the name suggests d stands for domain and in this scoring, we consider different domains and calculate the impact scholar has been able to create in these domains. The example ratings, work and results are also illustrated in the work below.

Table 1 :
Comparison Of Existing Ranking Techniques

Rating	Advantages	Disadvantages
h-index Hirsch (2005)	It accounts for the concept that having a greater number of works does not correspond to the quality of research.	It does not consider the whole research work of the scholar and compares with other ones in the same field. Citation count is taken into account, but works aren't actually being compared on the basis of citation count. This technique is neither adaptive nor can be universally applied to all scholars. It is greatly disadvantageous where scholars usually must struggle to get recognition for their work (Computer science).
I10-index	Easier to understand, calculate and interpret.	Does not focus on inter domain level scoring and gives a universal score to the author. Does not consider path - breaking research into account (Work with 10 citations and 2000 citations has the same impact).
G-Index (Egghe, 2006)	It accounts for authors top-performing articles. Difference between low performing and high performing authors is clearly visible.	Being an author level metric, it does not serve a purpose in research institutions where domain level research impact is usually taken into consideration considers all the research works of the scholar in that domain.

A. Working of rating process

Initially we need to assign citation count values as low, medium, high so as to make the algorithm more adaptive and statistically justifiable then we need to compute the rating of every work by comparing with all works resent in that domain and calculate in similar manner to all works, for computing the rating we use Glickman-2 algorithm and we compute rating for all works and take average rating of all individual rating and then assign rating in grade point average format.

The Glicko System, developed by Mark Glickman, is a rating system designed to assess the skill levels of players in two-player games. It is an extension of the Elo rating system and is known for its ability to dynamically adjust player ratings based on performance and the uncertainty associated with those ratings. The Glicko rating system consists of several key components and follows a specific mechanism for analysis:

Initialization: Each player is initially assigned a rating ®, a rating deviation (RD), and a volatility (σ). The rating represents the player's skill, the rating deviation indicates the uncertainty or confidence in the rating, and volatility measures how much the player's skill is expected to change.

Outcome Prediction: Prior to a match, the Glicko system uses the player's current rating and deviation to predict the expected outcome of the game against an opponent.

Game Result Submission: After the game is played, the actual result (win, loss, or draw) is submitted.

Rating and Deviation Update: The Glicko system updates the player's rating, deviation, and volatility based on the difference between the expected outcome and the actual result. Larger updates occur when there is a significant difference between expected and actual outcomes.

Opponent Adjustment: The updates also consider the skill of the opponent. Beating a stronger opponent has a different impact than beating a weaker one, adjusting the player's ratings accordingly.

Periodic Volatility Adjustment: The volatility (σ) is adjusted over time to reflect changes in a player's performance consistency. If a player's performance becomes more erratic, their volatility increases.

Time Decay: Ratings and deviations are subject to a time decay mechanism. The longer it has been since a player's last game, the more their rating deviation increases, reflecting the increased uncertainty about their current skill level.

Repeat Process: The above steps are repeated after each game, ensuring that player ratings are continuously updated based on their recent performance.

The Glicko System's analysis allows for a more nuanced and adaptive representation of player skill, considering not only performance but also the uncertainty and volatility associated with those performances. This makes it a valuable tool in competitive settings where player skills can change over time and where accounting for uncertainty is essential for accurate rating adjustments.

When comparing Glicko-2 with alternative ranking algorithms, it's essential to consider various factors to establish its superiority. Here's a comprehensive comparison framework:

- Accuracy and Predictive Power: Compare how well Glicko-2 predicts future outcomes compared to alternative algorithms. This could involve analyzing its Mean Squared Error (MSE) or other relevant metrics. Evaluate the extent to which Glicko-2 captures player skill changes over time and adapts to new data, especially in dynamic environments.

- Sensitivity to Performance: Assess how quickly Glicko-2 adjusts player ratings in response to changes in performance compared to other algorithms. Analyze whether Glicko-2 provides a balanced trade-off between responsiveness to recent performance and stability to avoid abrupt rating changes.

- Robustness to Outliers and Noise: Examine how Glicko-2 handles outliers and noise in player performance data compared to alternative algorithms. Test the resilience of Glicko-2 against intentional manipulation or random fluctuations in player ratings.

- Computational Efficiency: Compare the computational complexity of Glicko-2 with other algorithms. Consider factors such as processing time and resource usage. Evaluate Glicko-2's suitability for real-time or large-scale applications.

- Applicability to Different Scenarios: Analyze how well Glicko-2 performs in various scenarios, such as team-based games, individual player performance, and games with different rule sets. Compare its adaptability to diverse competitive environments compared to other algorithms.

- Ease of Implementation and Maintenance: Consider the complexity of implementing and maintaining Glicko-2 compared to alternative algorithms. Assess whether Glicko-2's parameters require frequent tuning or if it provides robust performance with minimal adjustment.

- Incorporation of Uncertainty: Evaluate how well Glicko-2's rating deviation reflects uncertainty in player skill estimation compared to other algorithms. Consider the robustness of Glicko-2's confidence intervals and how well they align with observed performance.

- Validation through Empirical Studies: Review published studies or conduct controlled experiments that directly compare Glicko-2 with alternative algorithms in specific contexts. Assess whether empirical evidence supports Glicko-2's superiority in terms of accuracy, stability, and adaptability.

- Adoption and Popularity: Consider the adoption rate of Glicko-2 compared to other ranking algorithms in competitive gaming or relevant domains. Analyze user feedback and testimonials from practitioners who have used Glicko-2 in real-world scenarios.

Flexibility and Customization: Evaluate how well Glicko-2 allows for customization to suit specific requirements or variations in different applications. Compare Glicko-2's flexibility in handling different rating scales, timeframes, and data characteristics with other algorithms.

4. Operational Procedure of the Rating System

By elucidating the working process, this section aims to provide a comprehensive understanding of the mechanisms employed in the rating system to evaluate and assign scores to entities or individuals. A general approach to calculating an impact score on a scale of 9 based on certain assumptions.

Step 1: Define the d-Impact Score and Scale: First, define what the "d-impact score" represents. Let's say it's a measure of the impact of a research paper or author's work on a scale of 1 to 9, where 1 represents low impact and 9 represents high impact.

Step 2: Data Collection: Collect relevant data for the research papers or authors being evaluated. This data could include metrics such as citations, journal impact factors, co-authorship networks, and any other factors considered indicative of impact.

Step 3: Determine Criteria and Weighting: Identify the specific criteria that will contribute to the d-impact score. Assign a weight to each criterion based on its perceived importance in measuring impact. For example, you might consider citations, media mentions, peer reviews, and collaborations.

Step 4: Normalize the Data: Normalize the data for each criterion to ensure that they are on a consistent scale. This could involve converting raw counts into percentages or standardized scores.

Step 5: Calculate Component Scores: For each paper or author, calculate a component score for each criterion by multiplying the normalized value by its

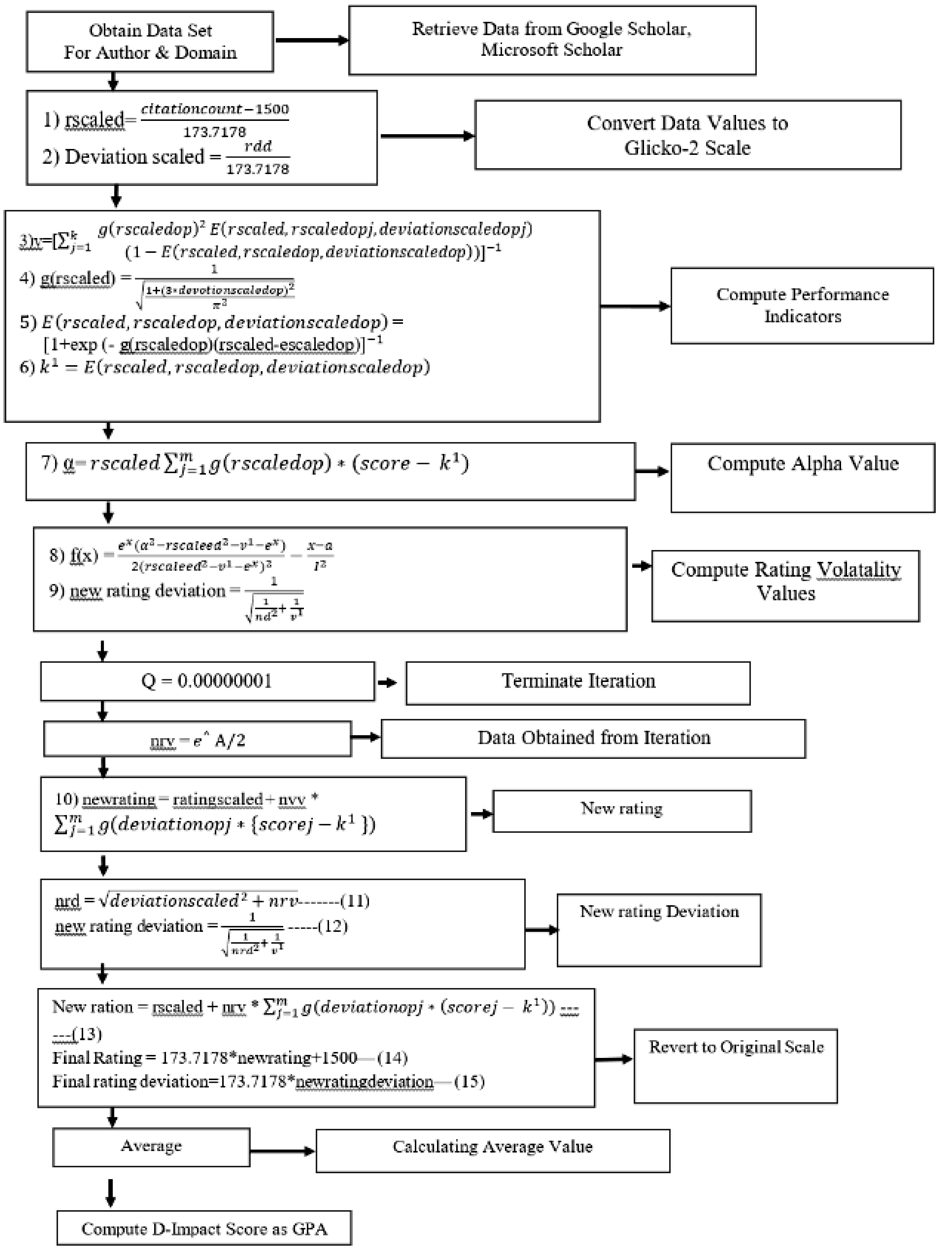

Fig. 1 : Operational Process of the Rating Technique

assigned weight. Sum these component scores to get an overall impact score for each paper or author.

Step 6: Convert to the 1-9 Scale: Normalize the overall impact scores to the 1-9 scale. To do this, you can use a mathematical transformation that maps the range of calculated scores to the desired scale. For instance, you could use a linear mapping or a more complex function to achieve this.

Step 7: Review and Validation: Review the calculated d-impact scores and ensure they align with your expectations of high and low impact. Validate the method using a sample of papers or authors whose impact levels are known or well-established. Adjust the weighting and normalization as needed based on the validation results.

Step 8: Interpretation and Reporting: Once you have calculated the d-impact scores for the research papers or authors, interpret the scores within the context of the defined scale (1 to 9). Clearly communicate the methodology, criteria, and transformation used to calculate the scores in any reports or presentations.

The procedure is as follows:

1. We consider individual citation count of every work and compare it with all works present in that domain and apply the Glicko-2 algorithm between individual works.

2. Initially convert players citation count and domain work citation count into Glicko-2 scale. (Default rating and rating deviation are 1500 and 350 and volatility is 0.2 and I'=0.2.

$$rscaled = \frac{citationcount - 1500}{173.7178} \quad (1)$$

$$deviation\ scaled = \frac{rdd}{173.718} \quad (2)$$

3. We need to update the rating of every work with Glicko-2 rating system r scaled, deviation scaled and compared results (0.25 for the win against a low scaled work, 0.5 for a win against a high scaled work and 1 for a win against the high scaled work, here winning refers to whether the participating author was able to outnumber opponent author's work citation count).

4. Computing the value of v' which is an estimated variance of work rating based on its performance with other works.

$$v = \left[\sum_{j=1}^{k} \frac{grscaledop^2 E(rscaled, rscaledopj, deviationscaledopj)}{(1 - E(rscaled, rscaledop, deviationscaledop))}\right]^{-1} \quad (3)$$

$$g(rscaled) = \frac{1}{\sqrt{\frac{1 + (3 * deviationscaled)^2}{\pi^2}}} \quad (4)$$

$$E(rscaled, rscaledop, deviationscaledop) = [1 + \exp(-g(rscaledop)(rscaled - eescaldop))]^{-1} \quad (5)$$

$$k' = E(rscaled, rscaledop, deviationscaledop) \quad (6)$$

5. Compute α, the estimated improvement in rating by taking consideration of previous rating and game outcomes.

$$\alpha = rscaled \sum_{j=1}^{m} g(rscaledop) * (score - k') \quad (7)$$

6. Determine the new rating volatility this requires iteration.

   Let us consider,

$$A = \ln(rv^2) \quad (8)$$

$$f(x) = \frac{e^x(\alpha^2 - rscaled^2 - v' - e^x)}{2(rscaled^2 + v^1 + e^x)^2} - \frac{x - a}{I^2} \quad (9)$$

The iterative algorithm:

1) Calculate the value of A using eq. 8.

2) If $\alpha^2 > deviationscaled + v'\ then\ set\ B\ as = \ln(\alpha^2 - deviationscaled^2 - v)$
3) Else
i) k1=1
ii) f(a-k1t) <0, then, set k1 as k1++, go to step 2 and repeat iteration set B=A-k1*t
iii) a1=f(A), b1=f(B)

4) While |B-A|> q carries out the following steps
i) C=A+(A-B) *a1/a1-b1 and c1=f(C)
ii) If c1*b1<0 then set A as B and a1 as b1 else set a1 as a1/2
iii) Set B as C and b1 as c1
iv) Stop if |B-A|<=q

5) After iteration stops set new rating volatility(nrv) as $e^{A/2}$

6) Update the rating deviation with above values

$$nrd = \sqrt{deviationscaled^2 + nrv} \quad (10)$$

7) Update both rating and rating deviation with new values rating new rating deviation

$$\text{New rating deviation} = \frac{1}{\sqrt{\frac{1}{nrd^2} + \frac{1}{v'}}} \quad (11)$$

$$newration = r\ scaled + nrv * \sum_{j=1}^{m} g(deviationopj * (scorej - k')) \quad (12)$$

8) Convert values back to original values

$$\text{Final rating} = 173.7178 * \text{newrating} + 1500 \quad (13)$$

$$\text{Final rating deviation} = 173.7178 * \text{new rating deviation} \quad (14)$$

9) Calculate the average rating value.

10) Calculate d-impact score as GPA for average rating value.

5. Experimental Evaluation

The proposed algorithm has been implemented in MATLAB 2018a with the system configuration of Intel processor Core i7, with 3.2 GHz of clock speed with 8GB DDR4 RAM and 1TB HDD. The results of the algorithm for author impactor score are clearly given in detail along with rating deviation and the average rating. By default, the average rating is given with 1500. As implementation proceeds the rating value changes so does the rating deviation and after computing rating and rating deviation after every work using Glicko-2 algorithm, here we take into account citation count of every work for comparing performance, then we calculate average rating and rating deviation values, we also calculate domain-specific highest values and compute d-impact score which is actually grade point average of every author with respect to top-performing author in the domain, the impact score signifies the performance of author in the scale of 9 points and has been evaluated for 62 different authors from 8 different domains, D-impact score is an accurate representation of author's performance in the domain it is also domain-specific hence named d-impact score.

Table 2: D-impact Score of Various Authors in Respective Domains

Author Name	Domain	Average Rating	Rating Deviation	D-Impact Score
A S Dzurak	Quantum Mechanics	1449	0.0374	6.52
E A Alsema	Environmental Engineering	1921	0.033	8.5
Daniel G Nocera	Environmental Engineering	1101	0.0372	5.505
Dave Money	VLSI	1280	0.0247	6.4
James W Tschanz	VLSI	1275	0.0187	6.375
Ruifeng Guo	VLSI	856	0.0297	4
Shyam P Murarka	VLSI	1300	0.0356	5.85
Siva G Narendra	VLSI	1365	0.0165	6.825
Terry Tao Ye	VLSI	650	0.045	3.25
Vivek De	VLSI	1500	0.046	7.5
Ali Keshavarzi	VLSI	1201	0.0317	6.75
Donna F Stroup	Alternative medicine	2000	0.059	8.5
Eugene Braunwald	Alternative medicine	1000	0.068	6
J Denis Mcgarry	Alternative medicine	600	0.072	4
Jack P Shonkoff	Alternative medicine	500	0.072	3.5
Jasvinder Singh	Alternative medicine	1500	0.064	8
Joseph T Hanlon	Alternative medicine	1430	0.074	7.2
P K Mukerjee	Alternative medicine	550	0.075	3.72
Isabelle Boutron	Alternative medicine	1650	0.032	8.5
Weiping Li	Control Systems	100	0.07	1
J M Maciejowski	Control Systems	520	0.084	3.04
Oussama Khatib	Control Systems	800	0.035	5
Domenico Casadei	Control Systems	750	0.046	4.7
G Serra	Control Systems	1000	0.098	6
J C Golinival	Control Systems	100	0.018	1
Joachim Holtz	Control Systems	800	0.035	5
Luca Zarri	Control Systems	700	0.063	4.5
Ludwig Wittgenstein	English Literature	500	0.085	3
Jerome John Mcgann	English Literature	450	0.076	2.8
John Barrel	English Literature	100	0.056	1
Laura Brown	English Literature	250	0.086	2
Nigel Fabb	English Literature	270	0.048	2.3
Robert Crawford	English Literature	265	0.052	2.5
Thomas Furniss	English Literature	300	0.049	3.15
Hao Zhang	Environmental Engineering	1000	0.0578	5.5
Hyung Chul Kim	Environmental Engineering	1078	0.078	5.51
Jan Vymazal	Environmental Engineering	2500	0.18	7.8
Mansour Samadpour	Environmental Engineering	300	0.0561	3.01
Pedro J J Alvarez	Environmental Engineering	3000	0.2	8.3
Vasilis Fthenakis	Environmental Engineering	1065	0.0671	5.56
Dave Evans	IOT	2500	0.071	7.5
David Tipper	IOT	2450	0.015	7.46

Author Name	Domain	Average Rating	Rating Deviation	D-Impact Score
Debasis Bandhopadya	IOT	2300	0.013	7.38
Hamid Sharif	IOT	2000	0.0125	7.2
Jurgen Jaspernite	IOT	1000	0.009	5
Mario Hermann	IOT	2300	0.014	7.38
Melanie Swan	IOT	1800	0.0156	6.3
Andrew Whitmore	IOT	1200	0.0318	6
George Pagangna	Organic Chemistry	2000	0.055	8
Jeongyong Lee	Organic Chemistry	1500	0.075	7.6
John E Roberts	Organic Chemistry	750	0.063	3
Joseph T Hupp	Organic Chemistry	2200	0.067	7.7
Karl A Scheidt	Organic Chemistry	1600	0.063	7.7
Omar K Farha	Organic Chemistry	1600	0.012	7.7
Sonbinh T Nguyen	Organic Chemistry	1700	0.027	7.8
J C C Hwang	Quantum Mechanics	750	0.034	3.5
J H Eberly	Quantum Mechanics	1600	0.016	7.2
J Ye	Quantum Mechanics	1500	0.0175	7
Marcos Rigol	Quantum Mechanics	1600	0.049	7.2
Maxim Olshanii	Quantum Mechanics	1800	0.063	7.5
Robert G Parr	Quantum Mechanics	2000	0.052	8
Vanja Dunjko	Quantum Mechanics	1600	0.035	7.7

6. Result Discussion and Author's Contribution

We have applied the methodology to various authors spanning across different domains, while this work is not intended to analyze every domain taken into consideration. Its main purpose is to look at research work as assign rating accordingly, hence it cannot analyze a domain and can only assign the score to an author. Hence these results are a representation of the author's work in a particular domain. The score is graded on a scale of 9 and D-impact score is also assigned to the same scale. As the grading is done on grade point average fashion, we initially find out the top performer according to citations in every domain and then assign the score accordingly to every author.

It is also important to note that for rating to work in efficient fashion it is important that we compare the research work of every author with as many works as possible (all works in the specific domain-if possible). It is also important that the opponent set consists of a wide range of data ranging from high cited works to less cited works which are the methodology we employed in the work. If the author wishes to improve D-impact score, the author should publish more works with more citations in the specific domain. Glicko-2 algorithms proposed by Mark. E. Glickman is quite a path-breaking algorithm used in many sports and game rating systems in this work we have applied the same rating methodology to the author rating systems. We have added adaptability to the technique by segregating dataset initially using distribution algorithms and also made results easier to interpret by applying grade point average mechanism. Future scope of Glicko-2 ranking process could be such as allowing users to fine-tune its parameters for specific contexts, to accommodate dynamic changes in player skill over time, measure and track the progress, and the actual development and adoption of Glicko-2 in these areas would depend on research, validation, and practical considerations.

7. Conclusion

This work proposes a model to acknowledge every author an impact with respect to their intended domain of research. Although several approaches are there for assigning an impact for every author there exists no such domain intended research impact factor for acknowledging the knowledge of an author in a particular research field. We used the Glicko-2 Rating system for identifying the research impact of the authors in their research domains. The results of the proposed model show the impact of every author in their respective domains. We used 8 different domains to address the authors which are picked in random, as the name suggests d-impact score is only domain-specific in nature and more accurate representation of scoring as it takes into account of all the works of author and assigns score in accordance to all the performances and is also adaptive as the approach is valid for all profiles across all different domains by taking into account low graded research work and also considering path-breaking research to evaluate author's performance in a specific domain, which is clearly a novel approach and useful one Hence we were able to conclude that this score is an improvement to techniques present in the field of research analytics.

Acknowledgment

The authors express their sincere gratitude to KLEF Vaddeswaram and MIT, Academy of Engineering, Alandi, Pune, for their invaluable insights, knowledge, resources, opportunities, and infrastructure that made it possible for this work to be published.

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