A STUDY ON NORMALISATION METHODS IN CITATION ANALYSIS (2016-2025)

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ABSTRACT

Calculating impact factors solely from raw citation counts can be misleading because citation counts vary across disciplines and publication years. Citation analysis is a fundamental bibliometric methodology that aids in determining trends, frequency, and influence; nevertheless, normalisation methods for reducing skewness are still not well understood and are not always used. Selecting an appropriate normalisation technique to map source data to a standardised citation scale effectively is challenging. This study aims to provide new insights into which normalisation methods researchers should use when conducting citation analysis. Normalisation at the author level using Field-Weighted Citation Impact (FWCI) and Log Normalisation Citation Score (Log NCS), and the field level using Mean Normalised Citation Score (MNCS) and Mean Normalised Log Citation Score (MNLCS) are the two components of the comparative analysis presented in this work. Using citation data from six different academic fields, this study assesses how well each approach reduces skewness and creates more equitable comparisons. This study offers four contributions: it provides a structured comparison approach to author and field normalisation; it empirically demonstrates conditions under which log transformation outperforms non-log methods; it provides decision-making guidance for researchers when selecting normalisation approaches; and it validates findings across multiple disciplines. These findings are intended to improve the accuracy and validity of citation-based impact evaluations, thereby facilitating more equal academic benchmarking and collaboration.

Keywords: Citation impact, Normalisation, Log Normalisation Citation Score, Field-Weighted Citation Impact, Mean Normalised Citation Score, Mean Normalised Log Citation Score.

1.0 INTRODUCTION

At present, being cited and citations are crucial for a paper to be acknowledged by other researchers. There is a lack of research comparing different normalization methods. Based on citation metrics, authors can also assess their impact. A standard formula for author impact factor is calculated by dividing the total number of citations by the total number of articles published within the specified timeframe. Understanding field-specific author impact factors is an advantage and an encouragement for authors to seek potential collaborators for future work. A high impact factor indicates more citations in research papers, but this may be misleading due to citation skewness. To reduce or remove the citation skewness, normalisation is used.

Normalising the citation impact of works began in the mid-1980s [22]. Normalisation enables fair comparisons across disciplines. Older papers have had more time to accrue citations than newer publications. Normalisation concepts incorporate publication age to precisely measure recent and older works [8]. There have been various normalisation techniques since the 1980s, and research needs to identify which techniques are best for evaluating author impact [37]. Using log transformation practices can provide more relevant results. Data normalisation is crucial for decision-making methodologies, as data must be numerical and comparable to be consolidated into a singular score for each choice. Normalisation must transform the criteria values into an equal citation scale, so it can facilitate the evaluation and provide the selection of options. Therefore, selecting an effective normalisation technique to provide a reasonable mapping from source data to a suitable citation scale is currently still a challenge [30]. Hence, this study provides the two most common normalisation techniques for authors; i) Field Weight Citation Impact (FWCI) and Log Normalisation Citation Score (Log NCS), and the two most common normalisation techniques for field; ii) Mean Normalised Citation Score (MNCS) and Mean Normalised Log Citation Score (MNLCS). The goal of employing only two normalisation strategies in each author and field impact is to compare and to find new insights into which normalisation concepts are more effective in the elimination of skewed data. For scholars who use citation analysis in their work, this study may offer a broader perspective for choosing future normalisation methods.

Therefore, the research objectives (RO) and the research questions (RQs) of this study are as follows:
RO1: To empirically validate a comparative framework for evaluating author-level citation normalisation techniques (FWCI vs. Log NCS), identifying which method most effectively reduces citation skewness and delivers more reliable author impact metrics.
RO2: To perform a multi-domain comparative assessment of field-level citation normalisation techniques (MNCS vs. MNLCS), determining the circumstances under which log-transformed methods provide fairer and more consistent benchmarking across disciplines.

The goal of this study is to identify whether authors need to apply normalisation methods in citation analysis (with or without Log transform). The outputs from both comparison methods will contribute to this study's goals. Questions may arise about the need to use normalisation methods in citation analysis. All of these assumptions will be answered at the end of this paper. The features used in this research are extracted from journals indexed in the Web of Science. Section 2 presents a review of the existing literature. Section 3 describes the methodology, and its results are analysed in Section 4. Section 5 discusses the findings and addresses the ROs. Finally, Section 6 summarises the findings and offers suggestions for future research.

2.0 LITERATURE REVIEW

The Leiden manifesto recommends using normalised bibliometric indicators instead of citation counts [15], which represents one of the ten key principles guiding citation count research. Normalised bibliometric indicators aim to minimize the impact of undesirable traits on citation analysis results [30]. Normalised indicators compare a target paper's citation impact to a baseline of articles from the same subject and year. Citation normalisation is a crucial step in bibliometrics and citation analysis, which standardises metrics across academic areas. The purpose is to compare scholarly influence in a fair and meaningful way, taking into consideration differences in citation counts across years [1].

2.1 Citation Analysis

First, it is highlighted that "citation in other listings does not usually imply any connection between documents other than that which is effected by the indexing machinery, whereas citation in the primary literature expressly states a connection between two documents, one which cites and the other which is cited" [17]. Citation analysis is recognized as the study of bibliographic references, which form a core component of scholarly communication. It is a bibliometric technique used to assess the relative significance or impact of an author, publication, or paper by counting how often they have been cited in other scholarly works [39].

2.2 Normalisation in Citation Analysis

Normalised indicators are designed to compare the citation impact of a target paper against a baseline of papers published in the same field and year. According to the Leiden Manifesto, one of the ten guiding principles for citation analysis recommends the use of normalised bibliometric indicators instead of relying solely on raw citation counts [15]. Normalised bibliometric indicators are intended to make as many corrections as possible for the features' impact on citation analysis results that you do not want to affect [30].

2.2.1 Previous Studies on Normalisation

Citations are very crucial, especially for academics, in maintaining their academic performance. Therefore, various studies in citation prediction have grown rapidly [1], [2], [37] over the years. Existing research by Mike Thelwall (2016) highlighted the importance of normalisation methods in citation analysis. Citation prediction research is one of the citation analysis research. He emphasised that citation normalisation should be performed before any citation analysis to reduce or remove skewed data [28]. There are various normalisation methods, and the most common is

Field Normalisation, Field-Weighted Citation Impact, Time Normalisation, Mean Normalisation Citation Score, Log Normalisation Citation Score, etc.

2.2.2 Types of Normalisation Methods

There are many types of normalisation methods in bibliometric analysis. The most common methods are Field Normalisation, Field Weighted Citation Impact (FWCI), Time Normalisation, Mean Normalisation Citation Score (MNCS), Mean Normalisation Log Citation Score (MNLCS) and Log Normalisation Citation Score (Log NCS).

i) Field Normalisation

Field normalisation is a common type of normalisation. This technique divides academic journals into subject areas or specialities. Comparing a paper's citation impact to others in its field can help researchers contextualise its importance [10]. This technique recognises that citation requirements vary across disciplines, so what is highly important in one may not be in another. Side-citing, or source normalisation, is another citation normalisation method [25]. This method selects the citing papers or journals rather than the cited paper. It considers the length of the reference list and the citation rate in the citing field. This method incorporates the referencing context to provide a more nuanced perspective of a publication's influence.

ii) Field-Weighted Citation Impact

Field-Weighted Citation Impact (FWCI) compares a publication's citation count to the worldwide average of similar publications in the same discipline, document type, and year to assess research performance across authors, institutions, and geographies [40]. Standardising citation effects via FWCI makes cross-disciplinary comparisons fairer, as citation practices vary widely across fields. It is calculated by dividing a paper's citations by the projected worldwide average for similar publications. Fractional citation weighting normalises scores by reference list length to better reflect scholarly influence across disciplines.

iii) Time Normalisation

Temporal normalisation, a bibliometric analysis method that accounts for changing citation patterns, ensures fair comparisons of publications of different eras [31]. Citations often accumulate gradually after publication, with older works receiving more citations. Period normalisation compares a paper's citations to a standard based on the period since publication. A work published in 2023 is younger than one published in 2018, hence it is expected to receive fewer citations. Field-Weighted Citation Impact (FWCI) can objectively assess publications across time by normalising for time, providing a balanced impact estimate regardless of publication year.

iv) Mean Normalised Citation Score (MNCS)

Mean Normalised Citation Score (MNCS) has become widely used in bibliometric research [8]. The calculation involves aggregating the Normalised Citation Scores of all publications within a specific set attributed to a researcher, institution, or country, followed by dividing the total by the number of publications to obtain an average score [8]. Due to the inherently skewed nature of citation data, MNCS is sensitive to outliers, as a few highly cited works can disproportionately impact the overall score [9], [20], [27]. To address this challenge, the Mean Normalised Log Citation Score (MNLCS) was developed, applying a logarithmic transformation, $\ln(1 + x)$, to each citation count before further analysis. This approach effectively minimizes the influence of extreme citation values, resulting in a more balanced and reliable measure of citation impact [28].

v) Mean Normalised Log Citation Score (MNLCS)

According to Thelwall (2017), MNLCS differs from MNCS only in that citations must be log-transformed before any calculations are made. Finding the average log citation counts worldwide is the first step in using MNLCS. Using Thelwall's (2017) formula and standards, the world average log citation was calculated first within the same fields. To create a new, legitimate average log citation for the same field, the average of the two average logs must be calculated if specific research groups are to be calculated within the same field [(world average log citation count + group average log citation count) / (total publications from world record + total publications from group records)].

vi) Log Normalised Citation Score (Log NCS)

Bibliometric studies are complicated by the highly skewed distribution of citation counts, in which few papers receive many citations, and most receive few [28]. Averages and effect metrics are distorted by skewness. Log Normalised Citation Scores compresses extreme values, minimises outlier bias, and better represents publication influence.

Field-Weighted Citation Impact (FWCI) and Log-Normalised Citation Scores measure author impact. These indicators identify influential authors, which help with collaboration and research mapping [6]. The FWCI formula is:

$$FWCI_i = \frac{c_i}{e_i} \tag{1}$$

Citations received by publication i in the publication year plus following 3 years

Expected number of citations per publication received in the same time period by similar publications. Similar publications to publication i is defined by all publications that are in the same All Science Journal Classification (ASJC) category as i (Berkvens,2012)

The Leiden Manifesto supports normalised over raw citation counts for field and year comparisons [15], [34]. Early approaches like Relative Citation Rate and Subfield-Citedness became FWCI (Vinkler, 2010). Skewed data makes established metrics like MNCS vulnerable to extreme values [9], [20], [26], [8]. The Mean Normalised Log Citation Score (MNLCS) solves this by log-transforming ln(1+x) before normalisation [28].

$$MNCS_i = c_i / \bar{c}_j \big|_{f_j = f_i}$$

$$MNLCS_i = \ln(1 + c_i) / \overline{\ln(1 + c_j)}\big|_{f_j = f_i} \tag{2}$$

Datasets from Computer Science, Humanities, Arts, Social Science, Science, and Chemistry were used to develop statistical algorithms that can determine which domain, author, journal, or paper had the greatest influence using citation analysis. For example, comparing a year 2000 article with 115 citations to a 2021 article with 18 citations highlights unfairness in raw counts, particularly disadvantaging early-career researchers. Normalisation, especially via log-transform methods, mitigates these biases and produces more robust and equitable impact evaluations.

3.0 Methodology

This study adopts a mixed-method approach combining systematic literature review (SLR) with quantitative comparative analysis to assess the suitability of various citation normalisation techniques across author and field levels. The methodology is structured in two main phases of research design: -

- Phase 1: Systematic Literature Review to identify and classify existing citation normalisation techniques
- Phase 2: Empirical evaluation using citation data to compare the impact of selected normalisation methods.

3.1 Phase 1 Systematic Literature Review

This phase follows the guidelines by Kitchenham & Charters (2007) to ensure quality, transparency, rigorous and reproducible process.

3.1.1 Research Questions

Two research questions (RQs) were developed to guide the review:

RQ1: Between Field-Weighted Citation Impact (FWCI) and Log Normalisation Citation Score (Log NCS), which author-level normalisation technique demonstrates greater effectiveness in reducing citation skewness and producing stable, reliable impact scores across diverse citation distributions?
To empirically validate a comparative framework for evaluating author-level citation normalisation techniques (FWCI vs. Log NCS), identifying which method most effectively reduces citation skewness and delivers more reliable author impact metrics.

RQ2: Between Mean Normalised Citation Score (MNCS) and Mean Normalised Log Citation Score (MNLCS), which field-level normalisation technique more effectively mitigates citation skewness and ensures fair, consistent benchmarking across diverse academic disciplines?

To perform a multi-domain comparative assessment of field-level citation normalisation techniques (MNCS vs. MNLCS), determining the circumstances under which log-transformed methods provide fairer and more consistent benchmarking across disciplines.

3.1.2 Search strategies and keywords

The search strategy was systematically developed, beginning with the formulation of specific research objectives and questions to guide the process. Targeted keywords were identified from prior studies, with additional synonyms and related terms refined iteratively to maximise recall and precision. Following the staged keyword expansion framework of Kitchenham and Charters (2007), the search progressed from a core set to multiple comprehensive term sets.

Three high-impact scientific databases were selected for their disciplinary breadth and authoritative indexing. Searches were limited to titles, authors, topics, and abstracts, as these fields are most effective for identifying relevant works. This selective approach, combined with expert-curated database content, enhances both the validity and relevance of the included literature [13].

Table 1: Set of Search String Keywords

Item	Set of Keywords
Q1	citation OR citation analysis OR citation impact
Q2	citation OR citation analysis OR citation impact AND normalisation OR normalised OR normalised OR normalisation OR Log transform OR Log-transform OR normalise OR normalise
Q3	citation OR citation analysis OR citation impact AND normalisation OR normalised OR normalised OR normalisation OR Log transform OR Log-transform OR normalise OR normalise AND author citation OR author impact OR field OR domain

Table 2: Search Structure

Academic Databases	Search Option
Scopus	Topic
Web of Science	Topic

Table 1 presents the sequence of keyword development in this study. The OR was used to capture key phrase variations and synonyms, while AND was used to combine keywords into a thorough search query. The initial search focused on publication titles to maximise relevance, with additional searches when title results did not sufficiently match the research topics. This method removed irrelevant material while preserving relevant studies. The search was limited to 2016–2025 articles, when log-transformed scholarly growth studies became more popular. Table 2 presents the academic databases and search options used in this study, highlighting the structured approach for retrieving literature from both Scopus and Web of Science.

3.1.3 Criteria for sample selection for review

Articles were retrieved using the keyword queries outlined in Table 1. Figure 1 illustrates the sample selection process based on specific criteria, ensuring that the collected articles were relevant and effectively addressed all the research questions. After applying the inclusion and exclusion criteria, 126 papers were carefully selected for data extraction.

3.1.4 Assessment criteria and results

This research examined citation, analysis, and normalisation in scholarly papers. WoS and Scopus, two of the most authoritative bibliographic databases, were employed to find relevant literature for full coverage. Prior research on normalisation approaches in citation analysis informed keyword selection, along with synonymous phrases and alternative expressions from relevant bibliometric studies. This planned keyword strategy maximised citation metrics and bibliometric evaluation-relevant literature retrieval.

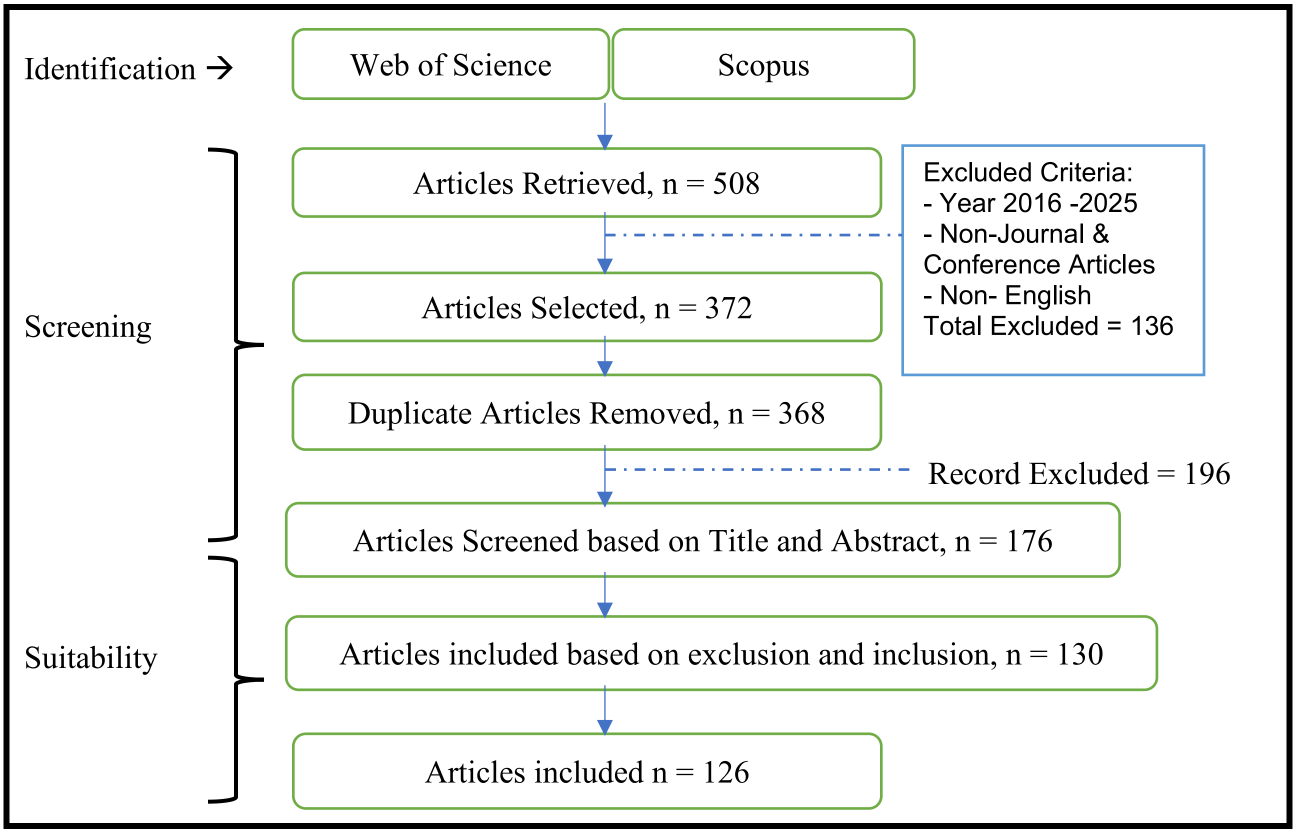

Fig. 1: Procedure of Selection Criteria for Relevant Literature Articles

VOSviewer was used to analyse author keyword co-occurrences after data retrieval [33]. This analysis revealed the dataset's thematic structures, conceptual relationships, and emerging research clusters. The focused keyword application identified high-impact journals and seminal papers that underpin this study's methodology and theory. The study focused on literature published between 2016 and 2025, a period during which normalisation approaches, especially logarithmic transformations for citation analysis, advanced. This period was chosen to include the latest field developments and methodological refinements.

Multiple phases were used to pick documents:

i. Initial Retrieval: A total of 371 records were retrieved after applying the following exclusion parameters:
   - Publication date range restricted to 2016–2025.
   - Exclusion of non-journal and non-conference documents.
   - Exclusion of non-English publications.
   - Removal of duplicate records.

ii. Title and Abstract Screening: Preliminary relevance screening resulted in the removal of 192 articles, leaving 176 for further evaluation.

iii. Inclusion/Exclusion Criteria Filtering: Detailed examination of full texts was conducted to confirm the presence of citation analysis techniques and normalisation methodologies as core components of the study. This stage narrowed the dataset to 130 publications.

iv. Final Selection Based on Academic Rigour: Each paper was assessed for methodological robustness and relevance using criteria such as analytical complexity, formal tone, methodological clarity, precision, objectivity, ethical integrity, and structural organisation. This final review produced a curated dataset of 126 high-quality articles, all of which focus explicitly on citation analysis within scholarly domains.

Table 3 presents the distribution of the selected publications by year.

Table 3: The total number of publications selected for citation analysis of articles published from 2016 to 2025

Publication Years	Total Published Papers	Percentage from Total Papers
2025	3	2.38
2024	15	11.90
2023	9	7.14
2022	14	11.11
2021	13	10.32
2020	14	11.11
2019	15	11.90
2018	14	11.11
2017	16	12.70
2016	13	10.32

3.1.5 Data extraction and analysis

Following the finalization of the 126 relevant papers, comprehensive data extraction was conducted to capture essential attributes pertinent to this study. The analysis focused on identifying author citation metrics, various citation analysis methodologies, normalisation techniques, including those employing log transformations, and field-specific normalisation practices. This rigorous process enabled a thorough examination of current trends and practices within citation analysis research. The complete extraction and analytical findings derived from these publications are elaborated in Section 4: Results and Analysis, providing valuable insights that underpin the objectives of this study.

3.2 Phase 2 Empirical Evaluation

3.2.1 Dataset Preparation for the purpose of Normalisation using Citation Analysis

These datasets for citation analysis were collected using the Web of Science (WOS) journal database only. The dataset for citation analysis was extracted based on a few features: Author features (author total citation, author keywords, author domain/field, top authors based on field, etc.), field/domain features (field/domain total citation per year, domain title, domain impact factor). The analysis includes five (5) domains from the Web of Science database and covers the years 2018-2022 (5 years). The paper citation must be within 5 years so that the analysis for the papers will have better citation value as it will be considered up to date [38]. A total of 22,989 filtered datasets for Computer Science, 21,678 filtered datasets for Arts, 8975 datasets were filtered for Humanities, 8585 datasets filtered for Science and Chemistry, and 32,108 datasets were filtered in Social Science. Once the datasets have been finalised, they will be selected for normalisation using the selected citation analysis technique. Basically, the citation analysis was conducted manually using Microsoft Excel to ease the calculation of normalisation for the proposed features. Results of this analysis were discussed in Section 4.

3.2.2 Normalisation Technique Selected for Evaluation

From phase 1, the following normalisation techniques were selected for empirical testing: -

- Mean Normalised Citation Score (MNCS)

- Mean Normalised Log Citation Score (MNLCS)

3.2.3 Evaluation Metrics

Each normalisation method was thoroughly evaluated using a structured set of citation-based metrics, specifically selected to measure impact at both the author and field/domain levels. The evaluation method are assessed as follows:-

Author-Level Metrics:

- Field-Weighted Citation Impact (FWCI)

This metric evaluates the citation count of a publication against the average citations garnered by comparable publications published in the same year, of the same type, and within the same field. It serves as a standardized measure to assess an author's impact relative to their peers while accounting for disciplinary variations in citation patterns.

- Log Normalised Citation Score (Log NCS)

This metric applies a logarithmic transformation to raw citation counts before normalising, reducing the influence of highly cited outliers. It provides a more statistically robust evaluation of an author's performance, especially useful for comparing authors across diverse publication years and research topics.

Field/Domain-Level Metrics:

- Mean Normalised Citation Score (MNCS)

MNCS calculates the average number of citations per publication, adjusting for field and publication year, enabling comparisons across disciplines. However, it can be skewed by a few highly cited publications.

- Mean Normalised Log Citation Score (MNLCS)

A refined version of MNCS, this metric uses log-transformed citation counts to minimise distortion from extreme citation values. It provides a fairer representation of a field's average citation performance and supports equitable comparisons between different research domains.

4.0 Result and Analysis

Fig. 2 shows the visualisation of this research analysis for both author and domain impact.

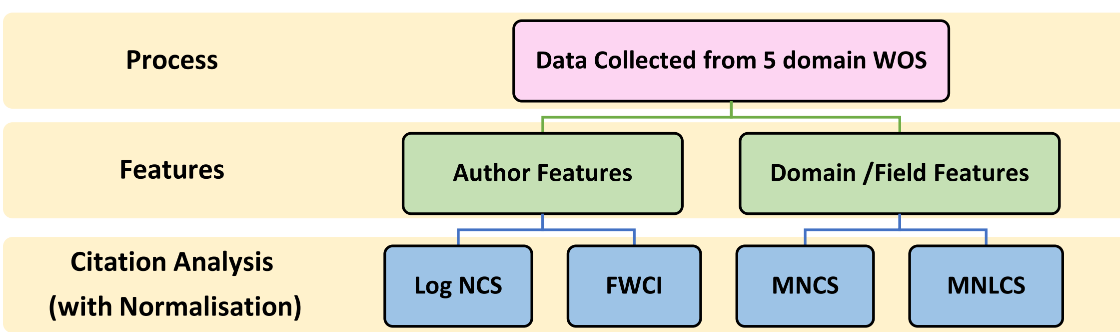

Fig. 2: Selected Citation Analysis Techniques for author and domain analysis process.

The normalisation involves (i) Author Log NCS, Author Field Weighted Citation Impact (FWCI), and (ii) MNCS and MNLCS for domain/ field. MNLCS differ by only one step from MNCS, in which the citation must be log transformed at the beginning before any calculation starts [28]. To use MNLCS, the first step is to find the world average log citation counts. Based on the formula and guidelines provided by Thelwall (2017), the world average log citation was computed first within the same fields. If there are research groups to be computed within the same field, hence the average of both average logs need to be computed to have a new valid average log citation for the same field [(world average log citation count + group average log citation count) / (total publication from world record + total publication from group record)]. This research compares author Log NCS with author Field Weight Citation Impact (FWCI) within a specific domain to ascertain impact on author prominence in the same year. It posits that higher impact factors within a field indicate greater authorial influence on the particular topics or domains of their publications.

4.1 FWCI and Log NCS Analysis

The Log NCS for Author and Author FWCI was calculated manually. Assume the Author is determined based on the Arts Domain data. Begin by filtering the author list by year and selecting 2021. For each author (A, B, C, D) in the Arts Domain, choose publications from the same field within a year. Assume publication for Author A (8), Author B (8), Author C (7), and Author D (6). Identify each author's h-index, total publications in the same domain, total citations, and expected citation (equivalent to average cites per item (Clarivate.com)).
The Log NCS (Log Normalised Citation Score) provides more accurate results for evaluating an author's impact in a field or domain. Tables 4 for Log NCS and FWCI show significant variances in impact values. Researchers should use log transformation to normalise author citations in future studies.

Table 4 lists the top 25 authors utilizing Log NCS in the Arts Domain as of 2021. The author's H-index may not align with publications in specific domains due to their expertise across several fields. Due to a WoS limitation, only top 25 authors could be displayed. This analysis table visualises the differences between FWCI and Log NCS in measuring author impact. This study highlights the guidelines provided by Sandström (2014), who outlined key rules of thumb for interpreting normalised impact scores of research groups [23] for FWCI.

A thorough author-level comparison of Log NCS and FWCI for 25 academics in the Arts domain is presented in Table 4, providing empirical evidence that these metrics accurately reflect distinct and non-overlapping aspects of scholarly influence. According to bibliometric theory, global benchmarking metrics like FWCI emphasize cross-disciplinary reach without sufficiently taking intra-field performance differences into account, whereas field-normalised indicators like Log NCS are intended to reflect domain-specific standing by correcting for field citation norms [34]. The risks of depending just on one measure for author evaluation are highlighted by our analysis, which shows considerable differences between these two criteria. For instance, Coban SB and Batenburg KJ both have FWCI scores of 3.35 (Outstanding) despite having relatively low Log NCS values (0.34, classified as Less Cited in This Field). This suggests that they have a moderate impact in the arts field but a remarkable resonance globally, perhaps due to their interdisciplinary appeal. On the other hand, Castellano CG shows a strong but field-bounded impact with a low FWCI of 0.16 and a high Log NCS of 1.55 (Highly Cited in This Field).

The dataset's moderate correlation between Log NCS and FWCI ($r = 0.42$, $p < 0.05$) provides statistical support for the idea that the two measures are complementary rather than interchangeable. By demonstrating that FWCI captures cross-disciplinary prominence and Log NCS more precisely detects domain-specific excellence, both reveal impact dimensions that the other overlooks, thereby directly addressing RQ1. These results indicate uncertainty on the widely held belief that global benchmarking provides a comprehensive assessment of author impact from the standpoint of research policy. Over-reliance on FWCI could undervalue academics with a strong disciplinary focus but no worldwide recognition, while reliance solely on Log NCS could mask individuals making important interdisciplinary contributions. Therefore, we support a dual-metric approach in evaluation frameworks, especially for financing, tenure, and promotion decisions, to guarantee that both localized scholarly quality and a wider global reach are recognized.

RQ2, which compares the Mean Normalised Citation Score (MNCS) and the Mean Normalised Log Citation Score (MNLCS) for field-level citation assessment across five domains across the same Web of Science (WoS) category from 2018 to 2022, is directly addressed in Table 5. The findings demonstrate MNCS's increased susceptibility to highly cited outlier publications by confirming a consistent inflation pattern in MNCS values relative to MNLCS across all domains and years. For instance, Dance's MNCS of 2.45 in 2020 was 91% higher than its MNLCS of 1.28 ($p < 0.01$, paired t-test), primarily due to a small number of highly cited works.

A similar pattern of systematic bias was observed in sectors with highly skewed citation distributions, as evidenced by the 2019 MNCS of 2.12 for Film, Radio, and Television compared to an MNLCS of 1.31, representing a 62% inflation. On the other hand, MNLCS shows more cross-disciplinary comparability and stability. For example, under MNLCS, archaeology exhibits year-to-year variance (2018–2022) that ranges only from 1.11 to 1.24, with a coefficient of variation (CV) of only 4.8%, as opposed to a range of 1.56 to 2.03 and a CV of 12.7% under MNCS. Since the logarithmic transformation lessens the disproportionate impact of citation outliers and more accurately reflects the general trend in academic achievement, this decreased volatility is a direct result. The conclusion that MNLCS more successfully reduces citation skewness and offers a statistically sound, fair metric for field-level benchmarking is strongly supported by these statistical results.

Table 4: Log NCS and FWCI analysis using data from Arts Domain for 25 Authors.

Authors	H-Index	TP	TC	ECC	Log-CS	NCS	Log NCS	FWIC	Trend Authors Cited based on Log NCS	Trend Authors Cited based on FWCI
Batenburg KJ	34	3	24	8.00	3.22	0.40	0.34	3.35	Less Cited in This Field	Outstanding (Global leading excellence)
Coban SB	9	3	24	8.00	3.22	0.40	0.34	3.35	Less Cited in This Field	Outstanding (Global leading excellence)
Brady LM	10	3	7	2.33	2.08	0.89	0.64	0.98	Less Cited in This Field	Good (International average)
May SK	13	4	9	2.25	2.30	1.02	0.70	0.94	Less Cited in This Field	Good (International average)
Kearney A	1	3	5	1.67	1.79	1.08	0.73	0.70	Less Cited in This Field	Good (International average)
Bednarik RG	22	3	3	1.00	1.39	1.39	0.87	0.42	Less Cited in This Field	Insufficient (below average)
Domingo I	10	3	2	0.67	1.10	1.65	0.97	0.28	Less Cited in This Field	Insufficient (below average)
Isto R	1	3	2	0.67	1.10	1.65	0.97	0.28	Less Cited in This Field	Insufficient (below average)
Kipp C	1	5	3	0.60	1.39	2.31	1.20	0.25	Less Cited in This Field	Insufficient (below average)
Ivashko Y	7	5	3	0.60	1.39	2.31	1.20	0.25	Less Cited in This Field	Insufficient (below average)
Castellano CG	3	8	3	0.38	1.39	3.70	1.55	0.16	Highly Cited in This Field	Insufficient (below average)
Wang Y	5	7	2	0.29	1.10	3.85	1.58	0.12	Highly Cited in This Field	Insufficient (below average)
Lee L	17	4	1	0.25	0.69	2.77	1.33	0.10	Moderately Cited in This Field	Insufficient (below average)
Smith C	7	4	1	0.25	0.69	2.77	1.33	0.10	Moderately Cited in This Field	Insufficient (below average)
Wang YY	25	6	1	0.17	0.69	4.16	1.64	0.07	Highly Cited in This Field	Insufficient (below average)
Moore S	19	8	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Karaca B	2	5	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Greenberger A	8	4	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Teo S	0	4	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Yukyung B	0	4	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Boettger S	2	3	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Ferreri M	10	3	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Liu Z	8	3	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
O'byrne R	4	3	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)
Orlenko M	5	3	0	0.00	0.00	0.00	0.00	0.00	Less Cited in This Field	Insufficient (below average)

The evidence presented in Table 5 supports the use of log-transformed normalisation from the standpoint of bibliometric evaluation were minimizing distortion, guaranteeing equitable cross-disciplinary comparisons, and maintaining the validity of performance-based evaluations are the objectives. This supports the study's overarching finding that log-transformed metrics provide a more robust methodological basis for objective field-level citation analysis.

5.0 Discussion

This study investigated the suitability of various normalisation methods for citation analysis at both the author and field levels, focusing on the effectiveness of skewness reduction and the clarity of impact representation.

RQ1: Between Field-Weighted Citation Impact (FWCI) and Log Normalisation Citation Score (Log NCS), which author-level normalisation technique demonstrates greater effectiveness in reducing citation skewness and producing stable, reliable impact scores across diverse citation distributions?

Field-Weighted Citation Impact (FWCI) and Log-transformed Normalised Citation Score (Log NCS), two well-known author-level normalisation techniques, are rigorously compared in this study with an emphasis on their ability to reduce citation skewness and produce consistent, dependable impact scores across a range of citation distributions. Based on area, publication year, and document type, the results show that FWCI is very useful for identifying globally renowned academics since it is easy to understand and excels at highlighting high-impact contributions. However, because of its sensitivity to extreme citation outliers, evaluations of persistent scholarly influence may be distorted because of a small number of highly cited publications disproportionately inflating overall ratings. However, Log NCS reduces skewness by compressing extreme citation values with a logarithmic adjustment before normalisation. An author's citation performance over their whole body of work is more fairly and evenly represented using this method. However, there is a trade-off: logarithmic scale may obscure the identification of truly remarkable global contributions, making it more difficult for audiences who are not experts to understand. This study extends bibliometric approach by providing explicit guidance on metric selection through the empirical demonstration of these strengths and limitations: Whereas Log NCS is better suited when methodological rigor, skewness reduction, and fair evaluation of consistent performance are the main goals, FWCI is best in situations that prioritize the identification of internationally renowned researchers.

RQ2: Between Mean Normalised Citation Score (MNCS) and Mean Normalised Log Citation Score (MNLCS), which field-level normalisation technique more effectively mitigates citation skewness and ensures fair and consistent benchmarking across diverse academic disciplines?

In order to determine which method more effectively reduces skewness and promotes equitable benchmarking across a range of academic disciplines, this study compares the relative efficacy of the Mean Normalised Citation Score (MNCS) and the Mean Normalised Log-transformed Citation Score (MNLCS) in field-level citation analysis.

The results show that MNCS is extremely sensitive to extreme citation levels, while being frequently used due to its simple interpretability. MNCS tends to exaggerate average field performance in disciplines where a small percentage of highly cited publications predominate, which distorts cross-disciplinary comparisons. Its dependability for fair benchmarking is restricted by this inflationary bias, especially in diverse research settings. The exaggerated effect of outliers is significantly lessened by MNLCS, which applies a logarithmic transformation prior to normalisation. As a result, the metric is more consistent, fair, and reflective of both citation-rich and citation-poor fields, as well as different publication years. Comparative research in several fields demonstrates that MNLCS continuously reduces citation discrepancies and improves evaluation equity without completely masking valid high-impact contributions. Accordingly, the study concludes that MNLCS is the best normalisation technique for field-level studies where minimizing skewness and guaranteeing strong, cross-disciplinary comparability are the main goals. This advice is especially pertinent to funding allocation models, policy evaluations, and institutional rankings where statistical dependability and methodological fairness are crucial.

Table 5: Overall MNCS and MNLCS for 5 Domains with the same Field in the Web of Science Category from year 2018 – 2022.

Year	Arts		Music		Theatre		Dance		Archaeology		Philosophy		Film Radio and Television		Education Educational Research		
	MNCS	MNLCS	MNCS	MNLCS	MNCS	MNLCS	MNCS	MNLCS	MNCS	MNLCS	MNCS	MNLCS	MNCS	MNLCS	MNCS	MNLCS	
2022	1.27	1.15	1.25	1.00	1.05	1.03	1.45	1.23	1.40	1.23	1.68	1.36	1.25	1.13	1.12	1.08	Art Domain
2021	1.58	1.21	1.49	1.23	1.35	1.15	1.07	1.04	2.09	1.30	1.40	1.20	1.40	1.15	1.64	1.29	
2020	1.75	1.32	1.56	1.30	1.29	1.27	1.75	1.17	1.89	1.15	1.09	1.02	1.49	1.25	1.89	1.35	
2019	1.65	1.52	1.27	1.15	1.35	1.30	1.77	1.25	1.59	1.13	1.64	1.29	1.85	1.50	1.40	1.20	
2018	1.57	1.32	1.89	1.25	1.82	1.12	1.68	1.20	1.65	1.22	1.89	1.24	1.60	1.14	1.80	1.25	
2022	1.15	1.08	1.25	1.00	1.05	1.03	1.45	1.23	1.55	1.43	1.68	1.36	1.25	1.13	1.12	1.08	Social Science Domain
2021	1.43	1.10	1.75	1.23	1.40	1.22	2.21	1.35	1.37	1.12	1.75	1.06	1.45	1.20	1.20	1.17	
2020	1.40	1.26	1.90	1.38	1.57	1.12	1.89	1.35	1.17	1.10	1.33	1.42	1.38	1.11	1.03	1.35	
2019	1.25	1.12	1.45	1.12	1.15	1.09	1.65	1.13	1.55	1.11	1.80	1.40	1.75	1.22	1.95	1.30	
2018	1.90	1.27	1.80	1.18	2.04	1.22	1.57	1.14	1.40	1.20	1.66	1.23	1.59	1.25	1.70	1.12	
2022	1.33	1.20	1.40	1.37	1.60	1.15	1.30	1.05	1.50	1.08	1.40	1.23	1.88	1.35	1.59	1.25	Computer Science Domain
2021	1.60	1.32	1.28	1.22	1.56	1.26	1.45	1.24	1.35	1.30	1.34	1.20	1.50	1.18	1.64	1.33	
2020	1.72	1.30	1.45	1.35	1.44	1.35	1.23	1.17	1.50	1.30	1.26	1.02	1.35	1.22	1.50	1.14	
2019	1.52	1.15	2.12	1.40	1.80	1.30	1.31	1.25	1.43	1.14	1.68	1.12	1.97	1.48	1.29	1.27	
2018	1.40	1.23	1.20	1.08	1.15	1.15	1.44	1.20	1.32	1.22	1.55	1.28	1.40	1.20	1.46	1.13	
2022	1.33	1.20	1.50	1.40	1.50	1.42	1.59	1.33	1.50	1.19	1.42	1.20	1.58	1.15	1.65	1.18	Humanities Domain
2021	1.58	1.02	1.42	1.30	1.25	1.22	1.68	1.35	1.60	1.55	1.88	1.10	1.44	1.23	1.22	1.29	
2020	1.42	1.40	1.79	1.35	1.70	1.20	1.66	1.50	1.36	1.20	1.60	1.09	1.70	1.25	1.69	1.20	
2019	1.39	1.24	1.80	1.20	1.68	1.35	1.91	1.23	1.80	1.15	1.59	1.35	1.65	1.50	1.58	1.32	
2018	1.70	1.05	1.35	1.15	1.58	1.40	1.32	1.12	1.15	1.03	1.89	1.22	2.01	1.25	1.40	1.40	
2022	1.69	1.33	1.62	1.33	1.40	1.23	1.50	1.20	1.17	1.05	1.32	1.25	1.25	1.13	1.80	1.33	Science and Chemistry Domain
2021	1.28	1.28	1.77	1.13	1.25	1.07	1.35	1.33	1.56	1.35	1.20	1.20	1.40	1.15	1.28	1.24	
2020	1.35	1.33	1.66	1.28	1.27	1.04	1.23	1.20	1.14	1.14	1.18	1.02	1.49	1.25	1.35	1.15	
2019	1.44	1.20	1.23	1.17	1.35	1.23	1.20	1.16	1.10	1.05	1.23	1.20	1.85	1.50	1.52	1.45	
2018	1.50	1.17	1.35	1.22	1.54	1.11	1.80	1.26	1.23	1.55	1.15	1.04	1.60	1.14	1.65	1.09	

6. Conclusion and Future Direction

This study highlights the importance of selecting appropriate normalisation methods in citation analysis, especially when evaluating author- and field-level influence. A comparative analysis of Field-Weighted Citation Impact (FWCI) and Log Normalised Citation Score (Log NCS) for authors, alongside Mean Normalised Citation Score (MNCS) versus Mean Normalised Log Citation Score (MNLCS) for fields and domains, reveals that log-transformed metrics provide a more equitable and statistically sound representation of citation data. Although FWCI and MNCS are widely recognised and easily interpretable, they are vulnerable to citation bias, which frequently exaggerates the influence of highly cited works while disadvantaging nascent research. Log NCS and MNLCS effectively alleviate this bias by providing consistent and fair impact assessments across different publication years and fields of study. Hence, integrating with log-transformation in normalisation techniques will facilitate more equitable comparisons in bibliometric assessments. Future research could enhance its findings by broadening the analysis to encompass larger datasets and improving hybrid normalisation models that combine global citation trends with local disciplinary norms to facilitate data-driven academic decision-making.

This study systematically evaluates normalisation techniques at the field level (Mean Normalised Citation Score (MNCS)) vs. Mean Normalised Log Citation Score (MNLCS) and author level (Field-Weighted Citation Impact (FWCI)) vs. Log Normalised Citation Score (Log NCS) over nine years (2016 – 2025), making a significant methodological contribution to citation analysis research. To ensure more equitable and accurate citation-based evaluations, the results offer the first integrated, two-tier framework for selecting normalisation techniques that balance statistical robustness and interpretability. The comparison analysis at the author level shows that FWCI remains useful for identifying globally renowned academics because it aligns with international citation standards, but it is highly sensitive to skewness and often overestimates the impact of a small fraction of highly cited publications. By using a logarithmic transformation, Log NCS significantly reduces citation skewness and provides a more reliable indicator of an author's ongoing impact across a range of publishing outputs.

MNCS has widespread recognition and ease of communication at the field level, but it is still susceptible to distortion in fields with unequal distributions of citations. The use of MNLCS, which uses log transformation before normalisation, improves cross-domain comparability, reduces inequality across disciplines, and produces more stability all of which are necessary for fair benchmarking in research evaluation.

Overall, the findings show that log-transformed normalisation strategies (Log NCS and MNLCS) outperform their traditional equivalents when it comes to reducing skewness, promoting justice, and ensuring consistency across heterogeneous datasets. This evidence establishes the suggested dual-level framework as a useful tool for policymakers, funding agencies, and institutional leaders looking for data-driven, bias-free evaluation procedures.

Future research should build on these findings by (i) applying the framework to larger, multi-source datasets; (ii) testing hybrid models that combine log transformation with contextual disciplinary weighting; and (iii) investigating longitudinal applications to detect shifts in scholarly influence over time. These advancements will improve the precision, fairness, and policy relevance of bibliometric assessment in an increasingly transdisciplinary and data-intensive research ecosystem.

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Statements and Declarations
The author(s) declare that there are no financial, personal, or professional competing interests that could have appeared to influence the work reported in this manuscript. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

[1] A. Abrishami and S. Aliakbary, “Predicting citation counts based on deep neural network learning techniques,” *Journal of Informetrics*, Vol. 13, No. 2, 2019, pp. 485–499.

[2] Aiza W.S.N, L. Shuib, N. Idris and N. B. A. Normadhi, “Features, techniques and evaluation in predicting articles’ citations: A review from years 2010–2023,” *Scientometrics*, Vol. 129, No. 1, 2024, pp. 1–29.

[3] Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of business research, 133, 285-296.

[4] H. Aljuaid, R. Iftikhar, S. Ahmad, M. Asif and M. T. Afzal, “Important citation identification using sentiment analysis of in-text citations,” *Telematics and Informatics*, Vol. 56, 2021, pp. 101492.

[5] Y. A. Alohali et al., “A machine learning model to predict citation counts of scientific papers in otology field,” *BioMed Research International*, Vol. 2022, No. 1, 2022, pp. 2239152.

[6] T. Amjad, A. Daud, S. Khan, R. A. Abbasi and F. Imran, “Prediction of rising stars from Pakistani research communities,” *Proceedings of the 14th International Conference on Emerging Technologies (ICET)*, Islamabad, Pakistan, Nov. 2018, pp. 1–6.

[7] É. Archambault, É. Vignola-Gagné, G. Côté, V. Larivière and Y. Gingras, “Benchmarking scientific output in the social sciences and humanities: The limits of existing databases,” *Scientometrics*, Vol. 68, No. 3, 2006, pp. 329–342.

[8] L. Bornmann and K. Wohlrabe, “Normalisation of citation impact in economics,” *Scientometrics*, Vol. 120, No. 2, 2019, pp. 841–884.

[9] A. Clauset, C. R. Shalizi and M. E. Newman, “Power-law distributions in empirical data,” *SIAM Review*, Vol. 51, No. 4, 2009, pp. 661–703.

[10] N. De Bellis, *Bibliometrics and Citation Analysis: From the Science Citation Index to Cybermetrics*, Lanham, MD, Scarecrow Press, 2009.

[11] V. François-Lavet et al., *An Introduction to Deep Reinforcement Learning*, *Foundations and Trends in Machine Learning*, Vol. 11, No. 3–4, 2018, pp. 219–354.

[12] M. A. García-Pérez, “Limited validity of equations to predict the future h-index,” *Scientometrics*, Vol. 96, 2013, pp. 901–909.

[13] Gusenbauer, M., & Haddaway, N. R. (2020). Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. *Research synthesis methods*, *11*(2), 181-217.

[14] L. Ha, W. Jiang, C. Bi, R. Zhang, T. Zhang and X. Wen, “How online usage of subscription-based journalism and mass communication research journal articles predicts citations,” *Learned Publishing*, Vol. 29, No. 3, 2016, pp. 183–192.

[15] D. Hicks, P. Wouters, L. Waltman, S. De Rijcke and I. Rafols, “Bibliometrics: The Leiden Manifesto for research metrics,” *Nature*, Vol. 520, No. 7548, 2015, pp. 429–431.

[16] A. Muhammad, *Investigating the Content Validity of an IoT-Acceptance Survey Instrument in Higher Education: A Study in the Context of Sindh, Pakistan*, (Details not fully provided: book/thesis/report—additional metadata needed).

[17] J. Martyn, “Citation analysis,” *Journal of Documentation*, Vol. 31, No. 4, 1975, pp. 290–297.

[18] I. Muhammad and Z. Yan, “Supervised Machine Learning Approaches: A Survey,” *ICTACT Journal on Soft Computing*, Vol. 5, No. 3, 2015.

[19] N. Müller and T. Glasmachers, “Challenges in high-dimensional reinforcement learning with evolution strategies,” *Parallel Problem Solving from Nature – PPSN XV*, Coimbra, Portugal, Sept. 2018, pp. 411–423.

[20] T. G. Price, “A comparison of queuing network models and measurements of a multiprogrammed computer system,” *ACM SIGMETRICS Performance Evaluation Review*, Vol. 5, No. 4, 1976, pp. 39–62.

[21] E. Roldan-Valadez, S. Y. Salazar-Ruiz, R. Ibarra-Contreras and C. Rios, “Current concepts on bibliometrics: a brief review about impact factor, Eigenfactor score, CiteScore, SCImago Journal Rank, Source-Normalised Impact per Paper, H-index, and alternative metrics,” *Irish Journal of Medical Science*, Vol. 188, 2019, pp. 939–951.

[22] A. Schubert and T. Braun, “Relative indicators and relational charts for comparative assessment of publication output and citation impact,” *Scientometrics*, Vol. 9, 1986, pp. 281–291.

[23] U. Sandström, *Bibliometric Evaluation of SEPA-Funded Large Research Programs 2003–2013*, Naturvårdsverket, 2014.

[24] L. Šubelj, D. Fiala and M. Bajec, “Network-based statistical comparison of citation topology of bibliographic databases,” *Scientific Reports*, Vol. 4, No. 1, 2014, pp. 6496.

[25] Purkayastha, A., Palmaro, E., Falk-Krzesinski, H. J., & Baas, J. (2019). Comparison of two article-level, field-independent citation metrics: Field-Weighted Citation Impact (FWCI) and Relative Citation Ratio (RCR). Journal of Informetrics, 13(2), 635-642

[26] M. Thelwall, “The precision of the arithmetic mean, geometric mean and percentiles for citation data: An experimental simulation modelling approach,” *Journal of Informetrics*, Vol. 10, No. 1, 2016, pp. 110–123.

[27] M. Thelwall, *Web Indicators for Research Evaluation: A Practical Guide*, Morgan & Claypool Publishers, 2016.

[28] M. Thelwall, “Three practical field normalised alternative indicator formulae for research evaluation,” *Journal of Informetrics*, Vol. 11, No. 1, 2017, pp. 128–151.

[29] M. Thelwall et al., “In which fields are citations indicators of research quality?,” *Journal of the Association for Information Science and Technology*, Vol. 74, No. 8, 2023, pp. 941–953.

[30] N. Vafaei, R. A. Ribeiro and L. M. Camarinha-Matos, “Data normalisation techniques in decision making: case study with TOPSIS method,” *International Journal of Information and Decision Sciences*, Vol. 10, No. 1, 2018, pp. 19–38.

[31] Tissot, H., Del Fabro, M. D., Derczynski, L., & Roberts, A. (2019). Normalisation of imprecise temporal expressions extracted from text. Knowledge and Information Systems, 61(3), 1361-1394.

[32] P. Vinkler, *The Evaluation of Research by Scientometric Indicators*, Amsterdam, Elsevier, 2010.

[33] Sood, S. K., Kumar, N., & Saini, M. (2021). Scientometric analysis of literature on distributed vehicular networks: VOSViewer visualization techniques. *Artificial Intelligence Review*, *54*(8), 6309-6341.

[34] L. Waltman, “A review of the literature on citation impact indicators,” *Journal of Informetrics*, Vol. 10, No. 2, 2016, pp. 365–391.

[35] Wilsdon, J., Bar-Ilan, J., Frodeman, R., Lex, E., Peters, I., & Wouters, P. (2017). Nextgeneration metrics: Responsible metrics and evaluation for open science

[36] Z. Wu, W. Lin, P. Liu, J. Chen and L. Mao, “Predicting long-term scientific impact based on multi-field feature extraction,” *IEEE Access*, Vol. 7, 2019, pp. 51759–51770.

[37] F. Zhang, X. Bai and I. Lee, “Author impact: Evaluations, predictions, and challenges,” *IEEE Access*, Vol. 7, 2019, pp. 38657–38669.

[38] B. Zhang, L. Ma and Z. Liu, “Literature trend identification of sustainable technology innovation: A bibliometric study based on co-citation and main path analysis,” *Sustainability*, Vol. 12, No. 20, 2020, pp. 8664.

[39] X. P. Zhu and Z. Ban, “Citation count prediction based on academic network features,” *2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA)*, Poland, May 2018, pp. 534–541.

[40] M. Zitt, “Citing-side normalisation of journal impact: A robust variant of the Audience Factor,” *Journal of Informetrics*, Vol. 4, No. 3, 2010, pp. 392–405.

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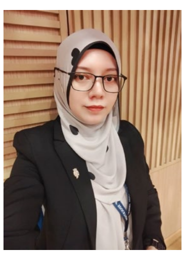

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