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Scholar Index for Research Performance Evaluation Using Multiple Criteria Decision Making Analysis

C. Ardil

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***Abstract*—**This paper aims to present an objective quantitative methodology on how to evaluate individual’s scholarly research output using multiple criteria decision analysis. A multiple criteria decision making analysis (MCDMA) methodological process is adopted to build a multiple criteria evaluation model. With the introduction of the scholar index, which gives significant information about a researcher's productivity and the scholarly impact of his or her publications in a single number (s is the number of publications with at least s citations); cumulative research citation index; the scholar index is included in the citation databases to cover the multidimensional complexity of scholarly research performance and to undertake objective evaluations with scholar index. The scholar index, one of publication activity indexes, is analyzed by considering it to be the most appropriate sciencemetric indicator which allows to smooth over many drawbacks of scholarly output assessment by mere calculation of the number of publications (quantity) and citations (quality). Hence, this study includes a set of indicators-based scholar index to be used for evaluating scholarly researchers. Google Scholar open science database was used to assess and discuss scholarly productivity and impact of researchers. Based on the experiment of computing the scholar index, and its derivative indexes for a set of researchers on open research database platform, quantitative methods of assessing scholarly research output were successfully considered to rank researchers. The proposed methodology considers the ranking, and the selection of data on which a scholarly research performance evaluation was based, the analysis of the data, and the presentation of the multiple criteria analysis results.

***Keywords*—**Multiple Criteria Decision Making Analysis, MCDMA, Research Performance Evaluation, Scholar Index, h index, Science Citation Index, Science Efficiency, Cumulative Citation Index, Sciencemetrics.

I. Introduction

SCHOLARLY research performance evaluation has always been the subject of active research in decision analysis terms. Decision analysis is the research of identifying and choosing alternatives based on the values and preferences of the decision maker. Decision analysis can be regarded as the mental/cognitive process of sufficiently reducing uncertainty and doubt about alternatives to allow a reasonable choice to be made from among them. Many decision situations involve multiple criteria in qualitative and quantitative domains. Such decision situations can be modeled as a multiple criteria decision making analysis (MCDMA) problem which involves making numerous and sometimes conflicting evaluations to come to a compromise in a transparent process.

C. Ardil is with the National Aviation Academy, Baku, Azerbaijan. https://orcid.org/0000-0003-2457-7261

The MCDMA method is an alternative approach, which provides a way to systematically structure and analyze complex decision problems. Multiple criteria decision analysis is both an approach and a set of techniques with the goal of providing an overall ordering of options. In multiple criteria decision analysis, values reflect human preferences and in particular the preferences of the decision maker involved in the specific decision context. There are many different multiple criteria decision analysis methods based on different theoretical foundations, such as optimization, goal aspiration, outranking, or a combination of these.

Multiple criteria decision analysis is a field of decision science and engineering, devoted to the development of decision support tools methodologies to address complex decision problems involving multiple criteria goals or objectives of conflicting nature. Multiple criteria decision analysis is founded on works carried out on expected utility theory, and on outranking relations.

Multiple criteria decision analysis is a general framework for supporting complex decision making situations with multiple and often conflicting objectives that stakeholders groups and/or decision makers value differently. Multiple criteria decision analysis is an umbrella term to describe a collection of formal approaches which seek to take explicit account of multiple criteria in helping individuals or groups explore decisions that matter. It is rooted in decision science research and support for single (or group) decision makers.

Multiple criteria decision analysis focuses on behavioral aspects of decision making, problem structuring procedures, methodologies for optimization under multiple objectives, multi attribute utility/value theory, outranking decision models, and preference disaggregation techniques for inferring decision models from data. Multiple criteria decision analysis is concerned with a variety of different types of decision problems, including deterministic problems, decision making under uncertainty and fuzziness, dynamic problems, and group decisions. Multiple criteria decision analysis is strongly linked with other quantitative disciplines such as computer science, artificial intelligence, and evolutionary computation.

Multiple criteria decision analysis introduces sound procedures for problem structuring and criteria aggregation, which can be used to rank and classify a set of alternative options or to choose the best ones. Except for the normative

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and descriptive aspects of decision making, Multi criteria decision analysis also adds a constructive perspective, in which a decision model is built through a progressive learning process that enhances the decision maker's understanding of the problem and ultimately facilitates the construction of a good model. Thus, a decision model is interactively constructed with the active participation of the decision makers, considering their system of values and judgment policy as well as their expertise on the problem under consideration.

The multiple stakeholder processes have recently been emphasized to structure decision alternatives and their consequences, to facilitate dialogue on the relative merits of alternative courses of action, thereby enhancing procedural quality in the decision making process.

Scholarly research performance analysis methodology has been absolutely transformed from a single objective simple system to a more complex system due to the inclusion of multiple benchmarks, stakeholders and disagreeing objectives. With the increase in the complexity and multiplicity in the problem of scholarly research analysis, the single objective optimization/analysis is no longer a prevalent approach.

Traditional single objective decision making which is basically concerned with either maximization or minimization of a particular element remains beneficial only in a study of small system. Current scholarly research performance analysis scenario has multiple objectives, definitions and criteria making it more difficult to attain a system with a perception of sustainability. Thus, an adequate scholarly research evaluation system considering necessary academic and scientific research aspects is essential to overcome rising demand of scholarly achievement recognition with a vision of sustainable research development.

To solve such complex problems concerning scholarly research evaluation, multiple criteria decision making is proved to be one of the better tools for efficient scholarly evaluation. Multiple criteria decision analysis basically originated from decision science research involving a wide range of methodologies, nevertheless with an amusing rational foundation in other disciplines. Multiple criteria decision analysis techniques have found wide application in public-sector as well as in private-sector decisions on decision intelligence, systems engineering, and decision engineering systems [1–3]. In the recent times, multiple criteria decision analysis has found its grounding application in engineering systems design and analysis [4-8].

Various technical methodologies and algorithms exist to evaluate and design systems based on optimization of either single or multiple criteria. The complexity involved in the various dimensions of scholarly evaluation systems with multiple stakeholders can be processed with multiple criteria decision analysis.

A. Multiple Criteria Decision Making Analysis

Decision analysis is a valuable tool in solving issue as characterized with multiple actors, criteria, and objectives. Multiple criteria decision analysis problems generally comprise of five components which are: goal, decision maker's preferences, alternatives, criteria, and outcomes respectively [1-3]. Multiple criteria decision analysis can be classified based on the number of alternatives under consideration, differences can be catered between multiple attribute decision making and multiple objective decision making; else both share similar characteristics. Multiple objective decision making is suitable for evaluation of continuous alternatives for which constraints in the form of vectors of decision variables are predefined.

A set of objective functions are optimized considering the constraints while degrading the performance of one or more objectives. In multiple attribute decision making, characteristics that are inherent are covered leading to consideration of fewer number of alternatives and thus evaluation becomes difficult as prioritizing becomes more difficult. The result is decided by comparing various alternatives with respect to each attributes considered [4-8]. Different multiple criteria techniques are applied in the field of scholarly research evaluation. Multiple criteria decision analysis models are another broader classification technique. The models developed are as per designer perspective. It can be a direct approach or indirect approach.

In direct approach the assignment of priorities or weights are done because of inputs from the beneficiary, society or acquaintance based on the survey. In an indirect method, all the possible criteria are separated in components and assigned weights as per previous similar problems, judgment of decision maker based on experience. There are many ways to classify multiple criteria decision analysis methods. According to the assumptions of preference elicitation and aggregation, multiple criteria decision analysis methods can be divided into two broad categories. A classification of multiple criteria decision models is also given as outranking models (noncompensatory) and utility models (compensatory). One refers to multiple attribute utility theory methods; the other refers to outranking methods.

Outranking methods are based on the principle that one alternative may have a degree of dominance over another, rather than the supposition that a single best alternative can be identified. Outranking is considered a partially compensatory technique that does not rely upon optimization. The ordering of alternatives provided by outranking methods may be incomplete since the methods allow for intransitivities in criteria weightings and for alternatives that are not considered comparable. Multiple attribute utility theory methods aim to associate a unique number (value) representing the overall strength of each alternative, taking all criteria into account. The basis of multiple attribute utility theory is the use of utility functions; whose purpose is to create a mathematical model to aid the decision process.

The utility theory is used in decision analysis to transform the raw performance values of the alternatives against diverse criteria to a common dimensionless scale. It gives decision makers the ability to quantify the desirability of certain alternatives and brings together different considerations in a structured way. Compared with outranking methods, multiple attribute utility theory methods present the advantage of simplicity and transparency, leading to a complete ranking of all the alternatives based on the decision maker's preferences.

Multiple criteria decision analysis is concerned with structuring and solving decision problems involving multiple criteria and numerical analysis of a set of discrete alternatives. It generally consists of three main operations, namely preference modeling, weight elicitation, and aggregation. Preference modeling focuses on capturing the decision maker's preferences for the specific decision context. There are two types of preferences, namely intra-criterion preferences and inter-criterion preferences. The former is judgements which refer to relative values attached to different levels of performances, while the latter is judgements which refer to the relative importance attached to the information carried by each single criterion. The values of judgements can be in ordinal, interval, or ratio scales. Ordinal scales on the overall preference values are sufficient if only the best alternative needs to be selected.

Decision problems involve criteria of varying importance to decision makers. The criteria weights usually provide the information about the relative importance of the considered criterion. Criteria weighting is a complex preference elicitation process, which can be classified in different ways (compensatory or noncompensatory). A variety of different methods for determining criteria weights in multiple criteria decision analysis have been developed, and different methods yield different weights. The criteria weights are generally treated as deterministic and are usually determined on a subjective basis. The uncertainty in the elicited weights can influence the resultant ranking of alternatives. Therefore, the procedures for deriving criteria weights should not be independent of the manner they are used and should be taken into consideration as part of the decision analysis process.

Aggregation refers to the process of combining several numerical values into one, so that the result of aggregation considers in each manner all the individual values. In multiple criteria decision analysis, aggregation operators are used to aggregate the different values of the utility functions. Multiple attribute utility theory methods include different aggregation models, but the most used one is the additive model. Additive aggregation is based on the mathematical concept of weighted means. However, different weighted versions (e.g., weighted arithmetic mean, weighted geometric mean, and weighted harmonic mean) may produce different aggregation results. Some performance values in multiple criteria decision analysis problems are often subjective and changeable.

Aggregation could yield inconsistent results since the weights of criteria and the scoring values of alternatives against the judgmental criteria always contain some uncertainties. It is an important issue how the final ranking or the ranking values of the alternatives are sensitive to the changes of some input parameters of the decision problem. Sensitivity analysis is a fundamental concept in the effective use and implementation of quantitative decision models. The purpose of sensitivity analysis is to assess the stability of an optimal solution under changes in the parameters. By knowing which criteria are more critical and how sensitive the actual ranking of alternatives is to changes on the current criteria weights, the decision makers can more effectively pay attention to the most critical ones. They can also make better decisions to the given multiple criteria decision analysis problem.

Multiple criteria decision making analysis is always complex due to involvement of multiple evaluation factors. This procedure remains controversial as objectives can lead to different solutions at different times based in the priority set by decision makers or analysts involved in the procedure. Moreover, a particular problem can be approached by different methods based on the defined functions. Every method or model has its own drawbacks and restrictions. A schematic procedure of multiple criteria decision making technique is illustrated in Fig. 1.

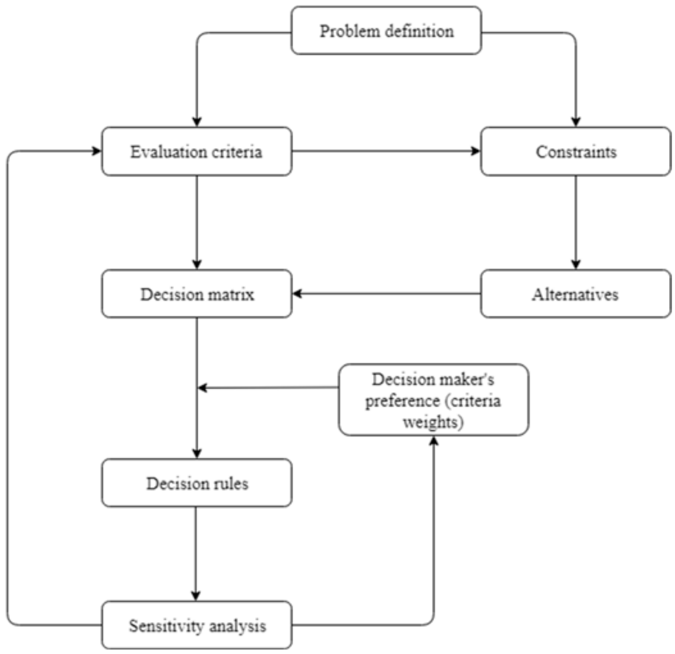

Fig 1. A schematic procedure for multiple criteria decision making analysis

B. Scholarly Research Analysis

Scholarly research performance success is basically attributed to individuals and not institutions or research groups. As these attributions can make or break a researcher's reputation, the road map of science is marked by countless disputes over the priority assigned to significant results of research. The most prestigious honor a scientist can receive is Open Science Award which is awarded for outstanding scientific achievement in several different disciplines.

Open Science Award can be quantitatively analyzed to provide an evaluation of most researchers. It is therefore customary to use scholarly research performance indicators to measure individual performance.

The scholar index was presented which gives information about the productivity of a scientist and the impact of his or

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her publications in one number (s is the number of publications with at least s citations). However, the scholar index is of only limited suitability for assessing a researcher's performance.

Analytical component of sciencemetrics is aimed at the triad of objects investigated: author, publication, journal. An array of data is processed using sciencemetric tools, and the major indicators obtained in this study are divided into two large groups: indicators reflecting the number of publications and those reflecting the number of citations per publication. Scholarly research performance analysis is based on two fundamental assumptions: (1) the results of important research are published in journal articles. The number of published articles refers to productivity of a researcher. (2) Each new piece of research should be closely linked to current or past research. These close references are marked by citations. As citations reflect the cognitive impact of the cited publication on the citing publication, the citations are considered as a measure of the scientific impact of a publication.

Citation analysis is the evaluation and interpretation of the citations received by publications, scientists, universities, countries, and other aggregates of scientific activity, used as a measure of scientific influence and productivity. Citation analysis is used to measure potential research impact. The list of references directing readers to prior relevant research is considered a fundamental part of any research publication. A reference or citation is a form of acknowledgment which one research publication gives to another.

Scholarly research is additive; scientists build on past work to discover new knowledge. To identify gaps in existing research and choose a research topic, researchers read the relevant published research and use this existing material as a foundation for arguments made in their own research publications.

The available digital literature databases enable researchers to search the number of publications and citations listed for individual scholars. Because both numbers (number of publications and citations) are linked to scientific practice and the data is readily available, the open digital scholarly databases have become the most important tools for evaluating individual researchers quantitatively. Evaluation research go further than merely giving the number of publications and citations for a researcher; numerous impact indicators are also used, allowing the multidimensional nature of scientific achievement to be captured in its complexity.

This study aims to present an objective quantitative methodology how to evaluate individual's scholarly researcher output using multiple criteria decision making analysis meaningfully. Evaluating individual scholarly performance is an essential component of research assessment, and outcomes of such evaluations can play a key role in institutional research strategies, including funding schemes, hiring, firing, and promotions. The proposed methodology relates to the selection of data on which an evaluation of this kind is based, the analysis of the data and the presentation of the results. The study was limited to the essential methods which are necessary and meaningful for the evaluation. To present the proposed methodology, the data extracted from Google Scholar for seven selected researchers who work in similar areas of research but are of different ages and enjoy different levels of academic success. The data is used only to illustrate the proposed methodology. For this reason, the researchers (R1…R7) are designated anonymously.

Multiple criteria decision making analysis helps a decision maker which quantifies particular criteria based on its importance in presence of other objectives. This work introduces some important features of the multiple criteria decision analysis, various algorithms available and highlights its various features in context to the scholarly research evaluation. The multiple criteria decision making analysis technique presented here can be used to find out an apt solution to the scholarly research analysis system design problems involving multiple and conflicting objectives.

The aim of this study is to develop a multiple criteria decision analysis technique for ranking decision alternatives. It is used as a quantitative decision method to assist decision makers in dealing with multiple criteria decision analysis problems. The proposed multiple criteria decision analysis model is based on the technique for order of preference by similarity to ideal solution is selected to choose the best compromise solution. It takes a compensatory aggregation approach for identifying the best alternative among the identified set of alternatives. The decision analysis technique is formulated from a decision matrix of preferences, and the criteria weights. The weighted normalized values are then used to aggregate preference information, as well as to rank the order of decision alternatives.

The remainder of this paper is organized as follows: Section 2 presents theoretical foundations, multiple criteria decision analysis and briefly discusses various objective weighting techniques available. It introduces the key performance indicators and scholarly research analysis model; Section 3 illustrates the application of multiple criteria decision making analysis model in scholarly research performance evaluation. Section 4 presents the discussion and conclusion.

II. Methodology

A. Research Design

The fundamental points which should be considered when carrying out research into the scholarly performance of individual researchers are introduced as follows:

a. Analysis of publications: A considerable number of publications is recommended as a basis for a statistical analysis of a single researcher. At the group level, it is deemed 10 to 20 publications per year appropriate. The minimum number of publications imply that an evaluated researcher should be at least at the postdoctoral level.

Therefore, it is possible to draw reliable conclusions regarding a researcher's citation record based on taking all the publications into account for the evaluation study. This

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solution implies that the evaluation does not focus on the current research performance, but the performance across the whole scholarly career.

b. Citation analysis: Everything a researcher has published before the evaluation should be included in the citation analysis. However, it should also be considered that it is difficult to evaluate the impact of the most recent publications reliably.

This evidence implies that citation-based indicators should be limited to assessing research published at least two years previously. Any attempt to use citation-based indicators for more recent research may result in spurious or misleading findings. Depending on the subject area, citations of a publication generally peak in the following two to five years before steadily decreasing in the following years.

Therefore, it is only after several years that it is possible to predict how the impact of a publication will develop.

c. Self-citations: In principle self-citations are usually an important part of the scientific communication and publication process and should therefore be considered in an evaluation study. A self-citation indicates the use of own results in a new publication. Researchers do this quite frequently to build upon own results, to limit the length of an article by referring to already published methodology, or simply to make own background material published in grey literature visible.

Only if the question of an evaluation study explicitly means to what extent a researcher has influenced other researchers' work, self-citations should be obviously ignored.

In every evaluation study, however, it should be checked whether a researcher cites him or herself excessively. The proportion which does not exceed approximately 30% is a reasonable level of self-citation.

B. Describing the Researcher

A study evaluating an individual researcher should include information about his or her career so which the open science metric results can be interpreted against this background. This information includes the institutions where a researcher has already worked or is currently working; the researcher's URL; degrees (MD, PhD, or MD/PhD); year of graduation; mentors during graduate school or post-doctoral fellowship; gender; and department(s) should be given in the evaluation report.

This study does not supply any open science metric information for the selected seven researchers who have been included as examples to preserve their identity.

C. Describing the Database

The database used as a rule in evaluative open science metrics is Google Scholar. It is a freely accessible web search engine which indexes the full text or metadata of scholarly literature across an array of publishing formats and disciplines. Google Scholar provides a simple way to broadly search for scholarly research literature.

Google Scholar provides citation counts for articles found within Google Scholar. Depending on the discipline and cited article, it may find more cited references than Web of Science or Scopus because overall, Google Scholar is indexing more journals and more publication types than other databases. Google Scholar is not specific about what is included in its tool, but information is available on how Google obtains its content. Limiting searches to only publications by a specific author name is complicated in Google Scholar.

Using Google Scholar Citations and creating your own profile will make it easy for a researcher to create a list of publications included in Google Scholar. Using Google Scholar Citations account, a researcher can see the citation counts for (his/her) publications and have Google Scholar calculate scholar index. Google Scholar can also be searched by author name and the title of an article to retrieve citation information for a specific article.

D. Describing the Software

Multiple criteria decision making analysis technique is used in this scholarly research performance evaluation. A special software was developed to analyze the data for this study.

E. Results

The scholar index is an index to quantify an individual's scientific research output. The scholar index is an index which attempts to measure both the scientific productivity and the apparent scientific impact of a scientist. The scholar index measures the impact of a particular scientist rather than a journal. It is defined as the highest number of publications of a scientist that received s or more citations each while the other publications have not more than s citations each [13-14].

The scholar index is based on the set of the researcher's most cited papers and the number of citations that they have received in other people's publications. The calculation formula of scholar index is simple: assume that N (N >1) is the total number of publications of an author. Let us presume which this author has a scholar index equal to s if s of his N research papers are cited at least s times each, while the rest (N - s) of the papers are cited no more than s times each. A scientist has index s if s of (his/her) Np papers have at least s citations each, and the other (Np - s) papers have at most s citations each. Otherwise speaking, an author has a scholar index equal to s if (s)he has s papers published, each of them cited at least s times. [12].

Moreover, the scholar index also considers total number of citations, distribution of papers in time, and duration of research relevance reflected in citations in other publications. It is important to note that the scholar index is an integer, so its dynamics is low, and its growth is determined by a significant set of factors. A single brilliant publication with hundreds of citations will not allow the researcher to have a high scholar index if there are no citations to other works of the same author, even though (s)he might have a high cumulative citation index. The scholar index provides a fair assessment of scholarly contributions made by authors who have dozens of citations to dozens of their papers created throughout many years.

The scholar index can also be applied to assess performance of an institution. Individual papers of individual authors recognized by the scholarly community (through multiple citations) provide a high cumulative citation index for the employer institution. However, notably high values of the scholar index are only available to those organizations where most authors perform research projects recognized by their global counterparts every year, have their results published on a regular basis, and have their publications consistently referred to in research papers of other authors.

The scholar index should be mainly used to decide on grant allocation or to confirm the status of a scientist. The scholar index is an integral tool of the most recognized multidisciplinary citation indexes. On these sciencemetric platforms, the scholar index may be calculated for any group of documents: publications of an individual author or a group of authors (for any period), a selected bulk of articles, publications of an institution, a country, or a research team.

The fact that scholarly databases use the scholar index as their indicator demonstrates that it has become a generally accepted tool to measure academic performance. The scholar index is one of the sciencemetric indicators (excluding total publications and total citations) which have been recently treated as certain criteria of research paper (or thesis) quality. A few studies investigate how the scholar index is applied to assess collective performance of a university or scientific institution.

The scholar index calculation algorithm is rather simple: all articles of an author (institution) are sorted from the highest to the lowest number of citations and go down the list until the position number of an article is higher than the number of its citations. The number of all the preceding articles is the scholar index [12].

The widely used scholar index and one of its variants, the m quotient is included because of its proliferation within the scientific community. The cumulative scholar index indicators are s_c (scholar index, g_1); s_5 (scholar index, g_2); s_p percentage, $s_p = 100(s_5 / s_c)$, g_3); the m value is a correction of the scholar index for time ($m = s_c / n$). m is an indicator of the successfulness of a researcher and can be used to compare researchers of different seniority. The m value can be seen as an indicator for scientific quality with the advantage as compared to the scholar index that the m value is corrected for career length.

$m = s_c / n$ (*m* index, and *n* is the number of years passed by after the first publication (research age), g_4).

A summary of the productivity and citation impact results for the eleven researchers is shown in Table 1.

Table 1. Decision Matrix of the Scholarly Research Performance Evaluation Problem

	Criteria	g_1	g_2	g_3	g_4
	Optimization	max	max	max	max
Researcher	R1	164	106	65	7
	R2	155	91	59	6
	R3	150	89	59	6
	R4	137	99	72	6
	R5	127	73	57	4
	R6	121	80	66	6
	R7	111	83	75	6

F. Multiple Criteria Decision Making Analysis Model in Scholarly Research Performance Evaluation

Multiple criteria decision analysis methods are successfully utilized in scholarly research performance analysis processes and are considered most suitable methods of solving issues related to scholarly research evaluation. The proposed method with focus on scholarly research evaluation is presented variedly and briefly. The model is used in combination with objective criteria weighting methods.

Fuzzy conversion scales may be used to convert a qualitative attribute into a quantitative attribute. The qualitative attributes, sensitivity analysis, and rank reversals may be considered while implementing the proposed method. Performing any type of sensitivity analysis, which is required in any multiple attribute decision making problem, enables decision maker to see how the changes in the weights of importance of the attributes affect the decision making process.

The idea behind proposed method lies in the optimal alternative being as close in distance as possible from an ideal solution and at the same time as far away as possible from a corresponding negative ideal solution. Both solutions are hypothetical and are derived within the method. The concept of closeness is later established and led to the actual growth of the compromise programming theory [9-11]. The stepwise procedure is given below:

Step 1: Construct the decision matrix:

After defining *n* criteria, and *m* alternatives, the decision matrix is established.

$$X = \begin{pmatrix} x_1 \\ \vdots \\ x_i \end{pmatrix} \begin{array}{c} \begin{array}{ccc} g_1 & & g_j \end{array} \\ \begin{pmatrix} x_{11} & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{pmatrix}_{ixj} \end{array} \tag{1}$$

where x_{ij} is the rating of alternative X_i with respect to criterion g_j .

Step 2: Construct normalized the decision matrix:

The normalized decision matrix is established. The normalized value n_{ij} is calculated from equation, where x_{ij} is the *i*th criterion value for alternative X_i ($i = 1,...,m$ and $j = 1,...,n$).

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{2}$$

where n_{ij} is the normalized criteria value.

Step 3: Construct weighted normalized the decision matrix:

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After assessing the utility function for each criterion, the integrated utility of each alternative is computed. Additive utility function is the simplest model in multiple attribute utility theory. In this model, the combined utility of the multiple objectives is the sum of the single utility functions multiplied by a scaling constant which reflects the importance of each objective within the decision context.

The normalized weighted values u_{ij} in the decision matrix are calculated using the values of the weight coefficients of the criteria, and which meet the condition that $\omega_j > 0$ and $\sum_{j=1}^{n} \omega_j = 1$ can also be used to determine the finite values of the criterion functions applying the expression.

$$u_{ij} = \omega_j n_{ij} \tag{3}$$

$$U_i = \sum_{j=1}^{n} u_{ij} \text{ ,, } i = 1,2,...,m \tag{4}$$

where ω_j represents optimal values of weight coefficients, while u_{ij} represents the normalized criteria values of alternatives according to optimization criteria in the initial decision matrix $X_i = [x_{ij}]_{mxn}$.

The calculation of the final values of the criteria functions (Q_i) for the alternatives is also performed. The values of the criteria functions are obtained from the sum of the normalized weighted values (u_{ij}) for the alternatives, or just the sum of the matrix elements ($U_i = [u_{ij}]_{mxn}$) in columns, using equation

$$Q_i = \sum_{j=1}^{n} u_{ij} \text{ , } i = 1,2,...,m \tag{5}$$

$$\sum_{j=1}^{n} \omega_j = 1 \text{ , } \omega_j \geq 0 \text{ , } j = 1,...,n \tag{6}$$

where Q_i denotes the utility of the *i*th alternative, ω_j denotes the weight of the *j*th criterion, and n_{ij} denotes is the normalized criteria values determined from single attribute utility functions on normalized scales. The decision makers should consider the
alternative with the highest integrated utility value.

Step 4: Determine the positive ideal A^+ (PIS) and negative ideal solution A^- (NIS)

The positive ideal A^+ (PIS) and negative ideal solution A^- (NIS) are derived from the weighted normalized decision matrix as shown below, where I and J are related to the benefit and cost criteria (positive and negative variables), $i = 1,2,...,m$, $j = 1,...,n$.

$$A^+ = \left\{u_1^+,...,u_n^+\right\} = \left\{(\max_i u_{ij} \mid j \in I), (\min_i u_{ij} \mid j \in J)\right\} \tag{7}$$

$$A^- = \left\{u_1^-,...,u_n^-\right\} = \left\{(\min_i u_{ij} \mid j \in I), (\max_i u_{ij} \mid j \in J)\right\} \tag{8}$$

Step 5: Determine the separation measures from the positive ideal solution and the negative ideal solution.

From the *n*-dimensional Euclidean distance, D_i^+ is calculated as the separation of every alternative from the ideal solution. D_i^- is calculated as the separation of every alternative from the negative ideal solution.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (u_{ij} - u_j^+)^2} \tag{9}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (u_{ij} - u_j^-)^2} \tag{10}$$

Step 6: Calculate the relative closeness to the positive ideal solution.

The relative closeness to the ideal solution of each alternative is calculated from:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{11}$$

Step 7: Rank the preference order.

After sorting the C_i values ($0 \leq C_i \leq 1$), the maximum value corresponds to the best solution to the problem.

G. Objective Weighting Methods

Since in the most real problems, the decision maker's expertise and judgment should be considered, subjective weighting is preferable, but when obtaining such reliable subjective weights is difficult, the use of objective weights may be useful. A combination of these two techniques is used to comprise both expert's opinion and the experimental facts. Use of subjective weights, objective weights, and the integrated weights (i.e., considering both the subjective and objective weights) may be useful. The critical inputs in multiple criteria decision analysis methods are to assign importance weights on the decision criteria. There are several ways to define the weights of the attributes. Nevertheless, most of the developed techniques fall into two main categories: subjective and objective weighting. Various methods for finding the weights of importance of the attributes can be categorized into two groups: (i) methods to find subjective weights and (ii) methods to find objective weights.

Subjective weights are determined according to the preferences of the decision maker. The methods to determine the objective weights of the attributes use the attributes' data for various alternatives without any consideration of the

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decision maker's preferences. Subjective methods rely on the expert-opinion while the emphasis of the objective methods is on the statistical evaluation of data given in a decision matrix. Each these techniques has its own advantages and disadvantages. Potential uncertainty in expert judgment is the main disadvantage of the subjective methods, while the objective methods do not benefit from the expertise and experience of designers.

To this end, six objective weighting approaches were chosen for the research performance evaluation problem.

a. Mean Index

The mean index requires minimal knowledge about priorities of criteria and minimal input of decision maker. If the decision maker has no information about true weights of criteria, then the true weights could be represented as a uniform distribution on the unit.

$$\omega_j = \frac{1}{n}, \quad j = 1,\ldots,n \tag{12}$$

$$\sum_{j=1}^{n} \omega_j = 1, \quad \omega_j > 0, \quad j = 1,\ldots,n \tag{13}$$

where ω_j is the objective weights of attributes which the mean weight method assigns.

The mean index assumes that all criteria are of equal importance, and thus weights of attributes are assigned to criteria equally via this method. Mean index is used in multiple criteria decision analysis when there is no information from decision maker or information is not sufficient to reach a decision. The method applied in many decision making problems requires minimal knowledge of the decision maker's priorities and minimal input from decision maker.

b. Variance Index

The Variance is the average of the squared differences from the Mean (μ_j). The variance procedure determines the objective weights of the attributes. The objective weight (ω_j) of the *j*th criterion is obtained by statistical variance

$$\sigma_j^2 = \frac{1}{m-1}\sum_{i=1}^{m}(n_{ij} - \mu_j)^2 \tag{14}$$

$$\omega_j = \frac{\sigma_j^2}{\sum_{j=1}^{n}\sigma_j^2} \tag{15}$$

$$\sum_{j=1}^{n} \omega_j = 1, \quad \omega_j > 0, \quad j = 1,\ldots,n \tag{16}$$

where, σ_j^2 is the sample variance of the *j*th attribute, n_{ij} is the normalized value of the *j*th attribute corresponding to the *i*th alternative, *m* is the number of alternatives, μ_j is the mean value of normalized data n_{ij} of the of the *j*th attribute, and ω_j is the objective weight of the *j*th criterion (attribute) which statistical variance assigns.

c. Deviation Index

The Standard Deviation (σ_j) is the square root of the Variance (σ_j^2). The standard deviation procedure determines the objective weights of the attributes. The objective weight (ω_j) of the *j*th criterion is obtained by standard deviation

$$\sigma_j = \frac{1}{m-1}\left[\sum_{i=1}^{m}(n_{ij} - \mu_j)^2\right]^{1/2} \tag{17}$$

$$\omega_j = \frac{\sigma_i}{\sum_{j=1}^{n}\sigma_j} \tag{18}$$

$$\sum_{j=1}^{n} \omega_j = 1, \quad \omega_j > 0, \quad j = 1,\ldots,n \tag{19}$$

where, σ_j is the sample variance of the *j*th attribute, n_{ij} is the normalized value of the *j*th attribute corresponding to the *i*th alternative, *m* is the number of alternatives, μ_j is the mean value of normalized data n_{ij} of the of the *j*th attribute, and ω_j is the objective weight of the *j*th criterion which standard deviation assigns.

d. Standard Index

The Standard Index uses an objective standard deviation approach to determine criteria weights. The procedural steps of the diversity weight method are as follows:

Step 1: Determine the mean values of normalized performances in relation to each criterion in the initial decision matrix $X_i = [x_{ij}]_{mxn}$.

$$\mu_j = \frac{1}{m-1}\sum_{i=1}^{m} n_{ij} \tag{20}$$

Step 2: Determine the value of the deviation

$$\sigma_j = \frac{1}{m-1}\left[\sum_{i=1}^{m}(n_{ij} - \mu_j)^2\right]^{1/2} \tag{21}$$

Step 3: Determine the degree of diversity

$$\delta_j = 1 - \sigma_j \tag{22}$$

Step 4: Determine the objective criteria weights

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$$\omega_j = \frac{\delta_j}{\sum_{j=1}^{n} \delta_j} \tag{23}$$

$$\sum_{j=1}^{n} \omega_j = 1 \text{ , } \omega_j > 0 \text{ , } j = 1,...,n \tag{24}$$

where, σ_j is the sample standard deviation of the jth attribute, n_{ij} is the normalized value of the jth attribute corresponding to the ith alternative, m is the number of alternatives, μ_j is the mean value of normalized data n_{ij} of the of the jth attribute, and ω_j is the objective weight of the jth criterion which standard index assigns.

e. Correlation Index

Criteria weights are affected as much from characteristics of the criteria as from subjective point of view of the decision makers. Such subjective weighting of the criteria is usually shaped by the decision makers experience, knowledge, and perception of the problem. However, this leads to doubt about reliability of the results. To overcome such problems, objective weighting approaches are used.

Correlation index is objective method for determination of criteria weights which includes the intensity of the contrast and the conflict that is contained in the structure of the decision making problem. It belongs to the class of correlation methods and is based on the analytical examination of decision matrix to determine the information contained in the criteria by which the alternatives are evaluated. In addition to the contrast intensity of attribute datasets in the decision matrix, the higher the level of interdependency between attributes, the larger the ranking outcome error.

Correlation index is an objective weighting method which can consider correlations between all given criteria. The correlation analysis method also included the contrast intensities by means of standard deviations of criteria and combined them with the weights from correlations. To determine the criteria contrast, the standard deviation of normalized criterion values by columns and the correlation coefficients of all pairs of columns are used.

Consider an initial decision matrix, $X = \left[x_{ij}\right]_{mxn}$, where x_{ij} is the performance measure of ith alternative with respect to jth criterion, m is the number of alternatives and n is the number of criteria. The first step in the application of the correlation coefficients method is to normalize the initial decision matrix using the following equation:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{25}$$

where n_{ij} is the normalized criteria value.

In the process of criteria weights determination both standard deviation of the criterion and its correlation between other criteria are included. In this regard, the weight of the jth criterion ω_j is obtained. The objective weight (ω_j) according to the correlation analysis method is expressed based on the characteristic conflict (R_j), the correlation of indicators (σ_{jk}), the amount of information (C_j), and the standard deviation
(σ_j). The calculated formulae were as follows:
Step 1: Find the correlation coefficient

ρ_{jk} calculated via the Pearson product-moments represents the correlation between the criteria j and k.

$$\rho_{jk} = \frac{\sum_{i=1}^{m} (x_{ij} - \overline{x}_j)(x_{ik} - \overline{x}_k)}{\sqrt{\sum_{i=1}^{m} (x_{ij} - \overline{x}_j)^2 \sum_{i=1}^{m} (x_{ik} - \overline{x}_k)^2}} \text{ ; } j \text{ and } k = 1,...,n \tag{26}$$

where m, $\overline{x}_j$ and $\overline{x}_k$ are the number of alternatives and the average values of criteria j and k, respectively. ρ_{jk} close to +1 or -1 indicates highly correlated criteria, while ρ_{jk} close to 0 indicates no correlation.

Step 2: Calculating the characteristic conflict

$$R_j = \sum_{j=1}^{n} (1 - \rho_{jk}) \tag{27}$$

Step 3: Calculating the amount of information

C_j is the quantity of information contained in jth criterion

$$C_j = \sigma_j R_j = \sigma_j \sum_{j=1}^{n} (1 - \rho_{jk}) \tag{28}$$

Step 4: Calculating the objective criteria weights

$$\omega_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{29}$$

$$\omega_j = \frac{C_j}{\sum_{j=1}^{n} C_j} = \frac{\sigma_j \sum_{k=1}^{n} (1 - \rho_{jk})}{\sum_{j=1}^{n} (\sigma_j \sum_{k=1}^{n} (1 - \rho_{jk}))} \text{ ; } j \text{ and } k = 1,...,n \tag{30}$$

The objective weight of the jth criterion (ω_j) is obtained.

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f. Entropy Index

In multiple criteria decision analysis, entropy relates to the degree of diversity within an attribute dataset. The greater the degree of the diversity, the higher the weight of that attribute.

In another words, the smaller the entropy within the data associated to an attribute, the greater the discrimination power of the attribute in changing ranks of alternatives. Entropy relates to incomplete information because it relates to the number of possible alternative results for a physical system after all the macroscopically observable information is recorded. The procedural steps for calculation of Entropy weights are as follows.

Step 1: Normalizing the decision matrix

Since measured data under different criteria can be of different units or scales, a given decision matrix should be first transformed into a dimensionless space:

$$p_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \ , \ i = 1,2,\ldots,m \ , \ j = 1,\ldots,n \tag{31}$$

where x_{ij} is an element of the decision matrix corresponding to the *i*th alternative and the *j*th criterion. *m* is the total number of alternatives, and *n* is the number of criteria.

Step 2: Calculation of the entropy (e_j) and the degree of diversity (d_j)

Entropy within the datasets of the normalized decision matrix for the *j*th criterion can be calculated

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{32}$$

The degree of diversity (d_j) is then calculated as

$$d_j = 1 - e_j \tag{33}$$

Step 3: Calculation of objective weights (ω_j)

The linear normalization of d_j to find the relative objective weight of each criterion:

$$\omega_j = \frac{d_i}{\sum_{j=1}^{n} d_j} \tag{34}$$

$$\sum_{j=1}^{n} \omega_j = 1 \ , \ \omega_j > 0 \ , \ \ j = 1,\ldots,n \tag{35}$$

where ω_j is the objective weight of the *j*th criterion which entropy method assigns.

III. Application

In this section, to demonstrate the applicability of the multiple criteria decision analysis technique on scholarly research performance evaluation problem, six objective weighting procedures (Mean Index (MI), Variance Index (VI), Deviation Index (DI), Standard Index (SI), Correlation Index (CI), and Entropy Index (EI)) are considered to conduct the sensitivity analysis. Four decision attributes (g_1, g_2, g_3, and g_4) are the beneficial criteria where higher values are desirable. Considering these evaluation criteria, the decision problem determines the optimum alternative from the selected seven alternatives.

A. Dataset

This study depends on the dataset related to seven scholarly researchers from similar domain of interest. The s_c index (cumulative impact) and s_5 index (five years impact) indicators were obtained from Google Scholar database as shown in Table 1.

B. Determining the objective weights of the performance evaluation criteria

Six different objective weighting methods were used to determine the weights of performance measures in the combined multiple criteria decision analysis method. The results obtained by using the procedural steps of the methods are given in the relevant figures and tables.

According to the explanations pertaining to the calculation processes of these methods, the objective weights of the criteria with respect to each related performance measurement were calculated by each weighting approach and the obtained results are illustrated in Table 2 to use in the MCDMA technique steps later.

Table 2. Objective Weights of Evaluation Criteria

Method	g_1	g_2	g_3	g_4
Optimization	max	max	max	max
Mean Index (MI)	0,25	0,25	0,25	0,25
Variance Index (VI)	0,2780	0,2292	0,1613	0,3316
Deviation Index (DI)	0,2658	0,2414	0,2025	0,2903
Standard Index (SI)	0,2492	0,2504	0,2525	0,2479
Correlation Index (CI)	0,2996	0,1602	0,3672	0,1730
Entropy Index (EI)	0,2492	0,2509	0,2531	0,2468

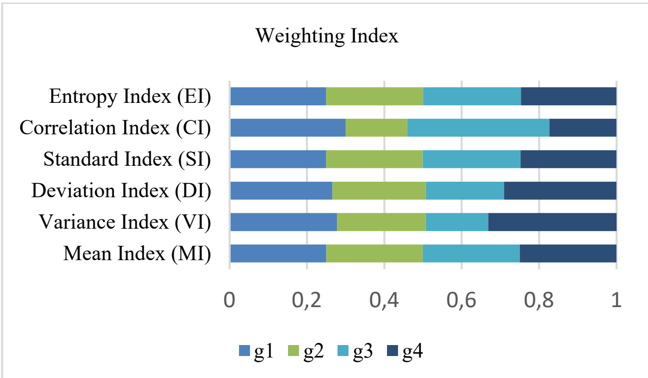

Fig. 1 Decision criteria weights determined by the weighting methods

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The final ranking results obtained using the multiple criteria decision making analysis technique and the six weighting methods are given in Table 3. The ranking results given in Table 3 also reflect the rankings of the alternatives when the proposed method and the weights obtained according to different weight determination methods are used.

Table 3. Final Ranking Order of the Researchers

Ranking Order in Weighting Index									
Weighting Index	MI	1	3	4	2	7	6	5	Ranking Order
	VI	1	2	4	3	7	5	6	
	DI	1	3	4	2	7	6	5	
	SI	1	3	4	2	7	6	5	
	CI	1	3	4	2	7	6	5	
	EI	1	3	4	2	7	6	5	
Researcher		R1	R2	R3	R4	R5	R6	R7	

In terms of sensitivity analysis, only the Variance Index (VI) gives different ranking results in accordance with the criteria weights it assigns. This effect of the Variance Index (VI) in the sensitivity analysis procedure is given in Table 4, using correlation analysis for the Pearson correlation coefficient / the Spearman rank correlation coefficient.

Table 4. Correlation Analysis for the Pearson Correlation Coefficient / the Spearman Rank Correlation Coefficient

	MI	*VI*	*DI*	*SI*	*CI*	*EI*
MI	1					
VI	0,93	1				
DI	1	0,93	1			
SI	1	0,93	1	1		
CI	1	0,93	1	1	1	
EI	1	0,93	1	1	1	1

According to the objective evaluation process of the proposed method, the R1 researcher shows the highest research performance ranking with the scholar index value it has achieved.

The citation rankings of researchers, strengths and shortcomings of the scholar index have been reported in various studies [15-37]. Despite being subject to much critical criticism, the Scholar Index is still used in scholarly databases to rank researchers in a particular research discipline.

The scholar index is based on a list of publications ranked in descending order by the times cited. The value of s is equal to the number of papers (N) in the list that have N or more citations. This metric is useful because it discounts the disproportionate weight of highly cited papers or papers that have not yet been cited.

A researcher (or a set of papers) has a scholar index of N if he/she has published N papers that have N or more citations each. The scholar index is based on times cited data from the database. It will not include citations from non-indexed resources. The scholar index is based on the depth of the user's subscription and the selected timespan, in that certain items may not be retrieved based on those parameters. Any record that is retrieved will include all the times cited for the article, whether the user has a subscription to all the citing articles.

As with all metrics based on citation, scholar index will vary by such factors as: time, subject area, and the number of papers. Users should be careful to make appropriate comparisons such as comparing scholar indexes within similar types of searches and/or similar subject areas.

Because the scholar index can be determined for any population of articles, it is difficult to provide overall benchmarks for the value of the scholar index. Very productive researchers in subject areas with high volumes of publication and citation can show scholar index values over 100 at the peak of their scientific careers. Newer researchers in smaller subject areas can have scholar indexes under 10.

a. *Strengths of the scholar index*

The scholar index reflects not just the number of papers, or the number of citations; it has some indication of the number of well-cited papers. This provides an interesting complement to other performance metrics, since it is not influenced by a single highly cited paper.

The scholar index is a metric for evaluating the cumulative impact of an author’s scholarly output and performance; measures quantity with quality by comparing publications to citations.

The scholar index corrects for the disproportionate weight of highly cited publications or publications that have not yet been cited.

Several resources automatically calculate the scholar index as part of citation reports for authors.

b. *Shortcomings of the scholar index*

The scholar index, like any other citation-based metric, is dependent on the subject area considered, as well on as the time since publication of important works. The scholar index in the citation report reflects citations as of the most recent database update, so it could vary upon subsequent analyses.

The scholar index is a metric to assess the entire body of scholarly output by an author; not intended for a specific timeframe.

The scholar index is insensitive to publications that are rarely cited such as meeting abstracts and to publications that are frequently cited such as reviews.

Author name variant issues and multiple versions of the same work pose challenges in establishing accurate citation data for a specific author.

The scholar index does not provide the context of the citations.

The scholar index is not considered a universal metric as it is difficult to compare authors of different seniority or disciplines. Young investigators are at a disadvantage and academic research disciplines vary in the average number of publications, references, and citations.

Self-citations or gratuitous citations among colleagues can skew the scholar index.

The scholar index will vary among resources depending on the publication data that is included in the calculation of the

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index.

The scholar index disregards author ranking and co-author characteristics on publications.

There are instances of "paradoxical situations" for authors who have the same number of publications, with varying citation counts, but have the same scholar index. As an example, Researcher A has eight publications which have been cited a total of 338 times and Researcher B also has eight publications which have been cited a total of 28 times. Researcher A and Researcher B have the same scholar index of 5 but Author A has a higher citation rate than Author B [15].

IV. Conclusion

This study provides significant implications regarding research performance evaluation of individual researchers based on the number of publications, citations, and scholar index. Organizations usually use the scholarly data and analysis based on those data to evaluate the research performance of individual researchers. In this study, Google Scholar open science data was used to perform the analysis while performing the research performance evaluation.

The study analyses a set of researchers (publications, citations, and scholar index) across four evaluation criteria. The size and importance of the research discipline is also a major factor, and it varies across the universities. Despite this limitation, the study contributes significantly to research, as this study is first time showing the impact of the scholar index on authors ranking in Google Scholar database across four evaluation criteria and showed empirically how the use of open science database provides a more comprehensive picture of an author's research rank.

The evaluation results also showed the listing in researchers ranking based on the number of publications, citations, and scholar index. The Google Scholar database only provides partial information for ranking evaluation. Other information was derived from the scholar index and m value.

Sensitivity analysis was conducted, and the evaluation results were compared to verify the robustness of the proposed MCDMA model which yielded reliable results. Consequently, the R1 researcher was ranked the best performing scientist. The proposed model can be considered as a reference for the future research performance evaluation problems. The findings of this study should not be taken literally but should be dealt with as decision support system when considering decision making problems using the MCDMA techniques.

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