

Analyzing Citation Dynamics and Forecasting Academic Trends: A Multi-Criteria Decision-Making Approach Using ARIMA and AHP

DeepakHajoary¹, Raju Narzary², Hem Chandra Das³, Rinku Basumatary⁴,
Kshirod Sarmah⁵

¹Department of Management Studies, Bodoland University, Kokrajhar, 783370, Assam,
India,

²Department of Computer Science and Technology, Bodoland University, Kokrajhar,
783370, Assam, India,

³Department of Computer Science and Technology, Bodoland University, Kokrajhar,
783370, Assam, India,

⁴Department of Computer Science and Technology, Bodoland University, Kokrajhar,
783370, Assam, India,

⁵Department of Computer Science, Pandit Deendayal Upadhyaya Adarsha Mahavidyalaya (A
Govt. Model College), Goalpara, 783124, Assam, India,

Corresponding Author: Deepak Hajoary

*Department of Management Studies, Bodoland University, Kokrajhar, 783370, Assam,
India, hajoary.deepak@gmail.com

Article History:

Received: 12-01-2025

Revised: 15-02-2025

Accepted: 01-03-2025

Abstract:

This study investigates the impact of publication age on citation counts and employs forecasting models to predict future publication trends. Citation dynamics are critical in bibliometric studies because they influence research visibility and academic recognition. Using a dataset of 505 academic publications from Scopus, this study applies correlation analysis, time-series forecasting (ARIMA), and multi-criteria decision-making (MCDM) techniques, particularly the Analytic Hierarchy Process (AHP). Pearson's correlation analysis revealed a weak negative correlation ($r = -0.154$) between publication year and citation count, indicating that older publications tended to have more citations, but other factors significantly influenced citation accumulation. Time-series forecasting using ARIMA (1,1,1) and Holt's Exponential Smoothing Model evaluated future publication trends, with ARIMA demonstrating higher short-term accuracy. The AHP model ranks research papers based on citation count, publication year, and relevance to MCDM, assigning higher weights to the citation count (63.3%). This study highlights the evolving role of artificial intelligence and big data analytics in bibliometric analysis and underscores the need for hybrid models that

integrate machine learning techniques with traditional decision-support frameworks. Future research should incorporate journal impact factors, author reputation, and open-access status to refine the citation prediction models. The findings contribute to a data-driven understanding of academic influence, providing insights for researchers, policymakers, and institutions aiming to enhance research visibility and scholarly impact.

Keywords: enhance, reputation, policymakers

Introduction

Publication Age and Citation Count Publication age significantly affects citation counts, making it a vital consideration in bibliometric studies, impacting wherein research is visible, scholars are recognized, and scholarly contributions remain relevant. [1]. Citation counts are considered a common metric of research impact [1], but the relationship between the age of publication and citation counts has been described as complex and influenced by many factors, both academic and otherwise [2]. By analyzing citation accumulation over time, we can better understand the relationship between publication year and citation accumulation [3]. Historically, the primary use of bibliometric analysis has been to measure and describe patterns in citation behavior, typically using statistical approaches to measure the relationship between certain characteristics of publications and the impact of those publications [4]. We address this issue in this study by using correlation analysis, time-series forecasting (ARIMA), and multi-criteria decision-making techniques, especially known as the Analytic Hierarchy Process, in combination as a multi-faceted methodology to assess and predict publication trends and influence over citations systematically [5]. This study is based on a dataset extracted from Scopus, which consists of 505 academic publications (including journal papers and conference proceedings) published in English [6]. The criteria were selected for MCDM topics related to AI, ML, and big data analytics, and they were focused on hybrid decision-support models [7]. This dataset enables a rich exploration of how research relevance, citation frequency, and publication year interact to define scholarly impact [8]. Considering the dynamic nature of academic research and the increasing emphasis on data-driven methods for decision-making, the goals of this study are as follows: to analyze the relationship between the year of publication and citation count to determine whether older publications have a tendency to attain more citations than newer publications; to use time series forecasting (ARIMA and Holt's Exponential Smoothing) to determine trends of future publications and study the performance of different forecasting techniques; to use the Analytic Hierarchy Process (AHP) to rank research publications in terms of their citation count, year of publication, and relevancy to MCDM, providing a systematic multi-criteria decision-making approach for the evaluation of academic impact [9]. Using a blend of bibliometric techniques and decision-support models, this study provides a comprehensive examination of citation dynamics and insights into a wider understanding of how academic research is assessed and valued over time [10]. The focus will be especially fruitful for

researchers, policymakers, and academic institutions that could benefit from data-driven approaches to make informed decisions to improve research visibility and scholarly impact.

Literature Review

The citation effect refers to the phenomenon in which highly cited papers continue to receive citations over time [11]. Citation patterns and publication trends indicate that older papers tend to accumulate more citations because of their cumulative impact. Bibliometric analysis is essential for understanding academic impact by examining these trends. Consequently, older publications accrue significant benefits. Recent studies suggest that characteristics such as journal impact factors, open-access status, and digital dissemination considerably affect citation counts. Multiple methodologies have been used to study citation dynamics, including Pearson's correlation coefficient for quantifying the association between publication year and citation count [12]. Earlier publications tend to have a higher number of citations on average, which are affected by factors including the relevance of the research performed and how citations are handled in each field, showing weak to moderate correlations in studies on the matter [13].

Time-series forecasting is a common technique for estimating publication dynamics in bibliometric analysis [14]. The Autoregressive Integrated Moving Average (ARIMA) model has been widely utilized for research output prediction, providing a formal framework for modeling publication growth patterns. Studies indicate that while the ARIMA model shows more promise for short-term fluctuations, Holt's Exponential Smoothing Model provides a more stable long-term projection[15].It is also well established in the existing literature that time-series forecasting accuracy is highly dependent on the selection of the model, and evaluation is generally done using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Akaike Information Criterion (AIC)[15]. Previous studies have shown that ARIMA methods generally perform better than simpler forecasting methods in terms of short-term publication trends but have the drawback of needing careful parameter tuning to avoid overfitting [16].MCDM techniques, especially AHP, have been extensively used to assess academic impact. The AHP helps compare publications based on multiple weight-adjusted criteria, allowing a more structured way of measuring publication impact than raw citations [17]. Another approach using AHP as a methodology for bibliometric evaluations includes metrics such as citation count, publication year, and topic relevance[18].The approach consists of building pairwise comparison matrices and assigning weights according to expert judgment, then carrying out criteria normalization to obtain ranking scores[19].The results suggest that citation count is the leading factor affecting research impact, followed by publication recency and subject relevance.Recent developments in artificial intelligence (AI) and big data analysis have generated opportunities for both automated citation analyses and predictive modeling in bibliometric research[20].For example, machine learning algorithms such as neural networks and natural language processing (NLP) continue to gain momentum for extracting insights from large-scale academic datasets, as studies show that AI-driven approaches can provide significant improvements for support-decision systems for academic evaluation, especially when combined with conventional MCDM methods[21].Hybrid

models combining AI with AHP and ARIMA have shown potential in refining citation predictions and ranking influential publications, highlighting the evolving role of computational techniques in bibliometrics[22].

Despite extensive studies on citation dynamics, forecasting, and MCDM methodologies, some gaps persist: (i) a limited intersection of hybrid models, which combine methodologies from bibliometric analysis, AI, and MCDM; (ii) open-access policies and digital visibility as underexplored drivers of citation trends, especially in early-stage publications; and (iii) a lack of cross-validation of forecasting models with various academic datasets. Future studies can introduce a bibliometric framework that is enhanced by AI, which can not only obtain the weight of the best indicators but also include citation predictions based on machine learning methods, combined with the MCDM methods described in this paper. Citation trends could be predicted better by generalizing our findings to other disciplines through further validation of forecasting models. Filling these gaps will improve future studies to provide a more accurate assessment of academic impact and a more data-driven approach to research evaluation.

Research Methodology

This study employs a quantitative research design to systematically investigate how publication age affects citation counts and to predict overall trends in the academic publishing arena [23]. To accomplish these goals, this study combines several methods, such as Pearson's correlation analysis, time-series forecasting based on the Autoregressive Integrated Moving Average (ARIMA)[23], and Multi-Criteria Decision-Making (MCDM) approaches, that is, Analytic Hierarchy Process (AHP)[24]. Data Collection and Preprocessing This study used a dataset obtained from searching the Scopus database with the search query: ("Multi-Criteria Decision Making" OR "MCDM") AND ("artificial intelligence" OR "machine learning" OR "big data analytics") AND ("hybrid models" OR "decision support systems" OR "automated decision-making"). This process resulted in 505 academic publications, including peer-reviewed journal articles and conference proceedings, all written in English from Scopus database.. We ensured that the studies were relevant to the MCDM area, focusing on AI and decision support systems. Two dependent variables were derived to test the hypotheses. Year of Publication (X): The year in which the research article was published. Citation Count (Y): The total number of citations received by a publication, as indexed by Scopus. Before conducting the analysis, the dataset was pre-processed to eliminate entries with missing values or incomplete citation metadata. This step ensured data reliability and enhanced the validity of the subsequent statistical analyses.

The following statistical methodologies were employed to evaluate the relationship between the age of publication and citation impact: Pearson's Correlation Coefficient was utilized to determine the strength and direction of the linear relationship between the year of publication and citation count. Covariance Analysis was conducted to examine whether citation counts increase or decrease with publication age. The standard Deviation was used to assess the dispersion of values in both the year of publication and the number of citations, indicating the extent to which these two variables deviate from the dataset.

Time Series Forecasting

To predict future publication trends, this study applies an ARIMA (1,1,1) model, defined as where:

AR (1): One autoregressive term,

I (1): First-order differencing to achieve stationarity,

MA (1): One moving average term.

The model was evaluated using the following metrics:

Root Mean Squared Error (RMSE): measures the average magnitude of the forecast errors.

Mean Absolute Error (MAE): Quantifies the average absolute difference between predicted and actual values.

Akaike Information Criterion (AIC): Balances the model fit and complexity.

A comparative analysis with Holt's Exponential Smoothing Model was conducted to determine the most suitable forecasting approach [25].

Multi-Criteria Decision-Making: Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) was used to find and rank impactful research publications according to the subsequent decision criteria:

C1 : Citation Count: 63.3%, measures academic impact of the publication.

C2 : Year of Publication (26.0%, considering recency and possible visibility)

C3 : Relevant to MCDM (Weighted 10.6%): The number of times each respective keyword appears in the title or abstract, designated by the authors.

A pairwise comparison matrix was developed using Saaty's basic 1–9 scale. The matrix was normalized, and weight priorities were calculated to evolve the sensitivity of the criteria [26]. The overall AHP score for each paper was computed as the weighted sum of individual normalized scores across all criteria.

The analytical framework used in this study can be summarized as follows:

Correlation Analysis: How relationships between publication age and citation frequencies are quantified.

Forecasting Comparison: A Comparative Analysis of the ARIMA and Holt's Exponential Smoothing Models. The Analytic Hierarchy Process (AHP) was employed to rank academic publications based on weighted criteria, thereby identifying those with the greatest scholarly influence. This integrated methodological framework, characterized by statistical rigor and structured decision-making, facilitates comprehensive analyses of citation dynamics and the forecasting of academic trends.

Results and Discussion

(i). Correlation Analysis Between Year of Publication and Citation Count

The inherent nature of bibliometrics is characterized by the aging of publications. Understanding this relationship elucidates citation dynamics, research visibility, and the lifespan of academic contributions. [27]. This study examined the publication year (X) to number of citations (Y) correlation to determine whether older papers accumulate more citations than new ones. One basic bibliometric aspect of papers is their citation count, which is affected by the age of the publication. The relationship between paper production and citation rates helps reveal citation dynamics, academic visibility, and citation persistence. To do so, this study seeks to assess the relationship between the year of publication (X) and the number of citations (Y), testing whether older publications receive more citations than more recent ones. There are two main numeric

variables in the dataset used in this study. The dataset used in this study includes two primary numerical variables:

X: Year of publication

Y: Citation count

Prior to analysis, missing values in either X or Y were removed to ensure data integrity. The statistical analysis was performed using Pearson's correlation coefficient, which quantifies the strength and direction of the linear relationship between these variables.

The mean values of Year of Publication (\bar{X}) and Citation Count (\bar{Y}) were computed as follows:

$$\bar{X} = (1/n) \sum X_i$$

$$\bar{Y} = (1/n) \sum Y_i$$

N represents the total number of papers analyzed, while X_i and Y_i denote the individual values of publication year and citation count, respectively

Results:

$$\bar{X} = 2016.69, \bar{Y} = 26.49$$

These values indicate that the average publication in the dataset is approximately 2016, while the mean citation count per paper is 26.49

Covariance measures the extent to which two variables change together and is given by:

$$\text{Cov}(X, Y) = (1/n) \sum (X_i - \bar{X})(Y_i - \bar{Y})$$

Computed Result:

$$\text{Cov}(X, Y) = -53.24$$

The negative covariance value suggests that citation counts tend to be higher for older publications.

The standard deviation of each variable is calculated as follows:

$$\sigma_X = \sqrt{\left(\frac{1}{n} \sum (X_i - \bar{X})^2\right)}$$

$$\sigma_Y = \sqrt{\left(\frac{1}{n} \sum (Y_i - \bar{Y})^2\right)}$$

Results:

$$\sigma_X = 6.73, \sigma_Y = 51.40$$

These values indicate that while publication years are relatively clustered, citation counts exhibit significant variation.

Pearson's correlation coefficient (r) is defined as:

$$r = \text{Cov}(X, Y) / (\sigma_X * \sigma_Y)$$

Substituting the computed values:

$$r = -53.24 / (6.73 * 51.40)$$

$$r = -0.154$$

Since r is negative, this confirms a weak negative correlation between the Year of Publication and Citation Count. The correlation coefficient ($r = -0.154$) indicates that, although older publications generally receive more citations, the strength of this relationship is weak and not significant. Several factors may account for this trend: 1. Cumulative Citation Effect: Older publications have a longer duration to accumulate citations, resulting in a higher citation count. 2. Field-Specific Citation Practices: Certain academic disciplines may prioritize older foundational papers over more recent ones. 3. Impact of Open Access and Digital Visibility: Newer papers may benefit from enhanced digital dissemination, which can counterbalance the temporal advantages of older papers. The weak correlation also suggests that additional variables, such as journal impact factor, author reputation, and research topic relevance, may have a more significant influence on citation counts.

(ii). Application of ARIMA for Forecasting Publication Trends

The Autoregressive Integrated Moving Average (ARIMA) model is a widely used statistical method for time-series forecasting, combining autoregressive (AR), differencing (I), and moving average (MA) components. Mathematically, the ARIMA (p, d, q) model is expressed as:

$$Y_t = c + \sum_{i=1}^p \phi_i Y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \epsilon_t$$

where:

Y_t represents the observed time-series value at time t ,

c is a constant term,

p denotes the number of autoregressive (AR) terms,

ϕ_i are the AR coefficients,

d is the degree of differencing applied to ensure stationarity,

q represents the number of moving average (MA) terms,

θ_j are the MA coefficients, and

ϵ_t is the error term (white noise).

For this study, an **ARIMA (1,1,1)** model was employed, where:

$p = 1$ (indicating one prior value is considered in the AR component),

$d = 1$ (indicating first-order differencing to remove trends and achieve stationarity), and

$q = 1$ (indicating one prior error term is included in the MA component).

Forecasting Results Using ARIMA

The ARIMA model was applied to the **publication count per year**, and the resulting forecast for the next five years is as follows:

$$\begin{aligned}\hat{Y}_{2025} &= 55.71 \\ \hat{Y}_{2026} &= 63.00 \\ \hat{Y}_{2027} &= 56.59 \\ \hat{Y}_{2028} &= 62.23 \\ \hat{Y}_{2029} &= 57.27\end{aligned}$$

The results indicate a fluctuating trend in the predicted number of publications, in contrast to the steady upward trajectory forecasted by Holt's Exponential Smoothing model. This suggests that publication growth may be influenced by external factors such as research funding, policy changes, or global academic trends.

(iii).Quantitative Evaluation of Forecasting Models

(i).Methodology for Model Evaluation

To assess the forecasting accuracy of the selected time-series models, the dataset was partitioned into two subsets:

Training Set: Comprising publication counts from 2015 to 2022.

Test Set: Containing data for the years 2023 and 2024, reserved for out-of-sample validation.

Two models were estimated using the training data:

Holt's Exponential Smoothing Model, incorporating an additive trend.

An ARIMA (1,1,1) Model, which includes autoregressive, differencing, and moving average components.

The accuracy of each forecasting approach was assessed based on key statistical metrics.

Evaluation Metrics

The performance of each model was evaluated using the following statistical measures:

Root Mean Squared Error (RMSE):

RMSE measures the average magnitude of forecast errors, penalizing larger deviations more heavily:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2}$$

where Y_t represents the observed values, and \hat{Y}_t denotes the model's forecasted values.

Mean Absolute Error (MAE):

MAE quantifies the average absolute differences between predicted and actual values:

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^n |Y_t - \hat{Y}_t|$$

Akaike Information Criterion (AIC):

AIC evaluates the trade-off between model fit and complexity, with lower values indicating a more optimal balance:

$$\text{AIC} = -2\ln(L) + 2k$$

where L is the model's likelihood function and k represents the number of estimated parameters.

Mean Absolute Percentage Error (MAPE):

MAPE assesses forecast accuracy in relative percentage terms; however, due to indexing limitations in the dataset, this metric was unavailable for computation.

Empirical Results and Interpretation

The computed error metrics for each model are summarized in the table below:

Model	RMSE	MAE	AIC	Forecast (Test Period)
Exponential Smoothing	18.45	16.62	125.65	2023: 37.40, 2024: 39.36
ARIMA (1,1,1)	16.75	13.43	205.34	2023: 42.58, 2024: 40.56

Model Accuracy

The ARIMA (1,1,1) model demonstrated superior forecast accuracy, as evidenced by its lower RMSE (16.75) and MAE (13.43) compared to the Exponential Smoothing model (RMSE = 18.45, MAE = 16.62). This suggests that ARIMA more effectively captures variations in publication trends.

Model Fit and Complexity

While ARIMA yielded more precise forecasts, the Exponential Smoothing model exhibited a significantly lower AIC (125.65 vs. 205.34), indicating a more parsimonious fit. This suggests that while ARIMA accounts for short-term fluctuations, Exponential Smoothing provides a more stable long-term trend projection. The results indicate a balance between the complexity of the models and their ability to predict the future. While both the ARIMA (1,1,1) and Exponential Smoothing models show good predictive accuracy, the ARIMA (1,1,1) provides better results than the Exponential Smoothing (in terms of RMSE and MAE) for the short term. Alternatively, Exponential Smoothing appears to fit the data in a less parameter-intensive manner (lower AIC), which may lend itself more favorably to performing long-term trending analysis. These results lead to the conclusion that model selection should be adjusted to the context of the forecasting goals. The ARIMA model is useful if the goal is primarily to anticipate year-over-year changes in publications. However, for estimating long-term growth, a simple forecasting model Exponential Smoothing is appropriate. Further studies may explore hybrid forecasting methods that combine the fluctuation adaptation ability of the ARIMA model with the stability mechanism of Exponential Smoothing on a smaller scale. The model may be improved with cross-validation and alternative ARIMA specifications such as ARIMA (2,1,2).

Analytic Hierarchy Process (AHP) Analysis of Research Papers

The AHP (Analytic Hierarchy Process) is a structured multi-criteria decision-making (MCDM) method that allows comparison and ranking of the alternatives based on multiple weighted criteria (Saaty, 1980). In this work, AHP is used to evaluate and rank academic research papers based on three input factors: citation count, publication year and AHP-related content. Specifically, we aim to weigh each criterion to derive a global ranking score for each paper in AHP. The dataset consists of research papers from various sources. The evaluation criteria are defined as follows:

Citations (C1) – Represents the academic impact of a paper; higher citations indicate greater influence.

Publication Year (C2) – More recent papers may provide updated methodologies and insights.

Relevance (C3) – Defined by the presence of keywords related to AHP in the title, abstract, or keywords section.

Each research paper is treated as an **alternative** in the AHP framework.

Pairwise Comparison Matrix Construction

The pairwise comparison matrix for the three criteria is constructed based on expert judgment using Saaty's fundamental scale (1–9). The assumed relative importance of each criterion is given below:

$$A = \begin{bmatrix} 1 & 3 & 5 \\ \frac{1}{3} & 1 & 3 \\ \frac{1}{5} & \frac{1}{3} & 1 \end{bmatrix}$$

where:

Citations (C1) is strongly preferred over Publication Year (C2) (value 3) and Relevance (C3) (value 5).

Publication Year (C2) is moderately preferred over Relevance (C3) (value 3).

Normalization and Criteria Weights Calculation

Each element of the matrix is normalized by dividing by the column sum, yielding the normalized comparison matrix:

$$A_{\text{norm}} = \begin{bmatrix} 0.633 & 0.692 & 0.625 \\ 0.211 & 0.231 & 0.375 \\ 0.126 & 0.077 & 0.125 \end{bmatrix}$$

The priority weights (w) for the criteria are obtained by computing the mean of each row:

$$w = \begin{bmatrix} 0.633 \\ 0.260 \\ 0.106 \end{bmatrix}$$

Thus, the computed importance weights are:

Citations (C1): 63.3%

Publication Year (C2): 26.0%

Relevance (C3): 10.6%

AHP Score Calculation

Each paper is scored using the following formula:

$$S_i = w_1 \cdot C_1 + w_2 \cdot C_2 + w_3 \cdot C_3$$

where:

S_i is the AHP score of paper i .

C_1, C_2, C_3 are the normalized values of citations, publication year, and relevance, respectively.

w_1, w_2, w_3 are the corresponding criteria weights.

The final AHP scores are computed, and the papers are ranked accordingly.

The top-ranked papers based on the computed AHP scores are presented in Table 1.

Table 1: Ranked Research Papers Based on AHP Analysis

Rank	Research Paper Title	AHP Score
1	A state-of-the-art survey & testbed of fuzzy AHP	0.829
2	Intuitionistic fuzzy Bonferroni means	0.802
3	Designing an integrated AHP-based decision support system	0.779
4	Integrated QFD-MCDM framework for green supplier selection	0.690
5	Fuzzy AHP-based decision support system for security	0.680
6	Role of multiple stakeholders and the critical success factors	0.611
7	Multi-criteria decision support system for wind energy planning	0.560
8	GIS-based comparative assessment of flood susceptibility	0.548
9	A Decision Support System methodology for selection of alternatives	0.546
10	Generalized hesitant fuzzy sets and their applications	0.534

The highest-ranked paper, "A state-of-the-art survey & testbed of fuzzy AHP," obtained an AHP score of 0.829, indicating its strong academic impact based on citation count and relevance. Similarly, other highly ranked papers demonstrate a balance between citation influence, recent publication date, and keyword-based relevance. The empirical AHP-based ranking of research articles showed that academic influence is most positively affected by the number of citations, followed by the date of publication and relevance of the subject [28]. The AHP method provides a systematic method of assessment in the academic literature, which is useful for identifying key contributions in a given area of study. Future work includes implementing the weighting process using expert opinion and additional considerations such as journal impact factor.

Conclusion

This study analyzed the relationship between publication age and citation counts using a combination of Pearson's correlation analysis time-series forecasting (ARIMA) and Multi-Criteria Decision Making, such as Analytic Hierarchy Process MCDM. The analysis indicates the presence of a weak negative correlation ($r = -0.154$) between publication year and the number of citations, which also implies that older publications have more citations, but the strength of the said correlation is small. In addition, citation dynamics are influenced by other variables, such as research visibility, accessibility, and field-specific citation practices. When compared with Holt's Exponential Smoothing model, the ARIMA model

outperformed it in short-term forecast accuracy, which is useful in deciding on the forecasting method. Data used for training: Academic research papers ranking model based on AHP-type decision-makers in the fields of Social and Health Sciences AHP model was used as the method for evaluating it while satisfying the multi-criteria weighing. Through factor evaluation, it was found that the most common determining factor was citation count as an argument that determines academic influence. In conclusion, this study adds depth to our understanding of citation dynamics and the shift towards diverse markers of scholarly impact. These findings highlight the need to incorporate a new lens of analysis — a collection of statistical modeling and decision-support techniques — that provides a more nuanced understanding of research impact and predictions of evolving academic trends. Enhancing research analytics across academic, corporate, and research landscapes, recognizing the myriads of attributes contributing to research outcomes, and predicting the next big research trends. Future Research Directions Several key advances and refinements can enhance future research on citation dynamics and academic forecasting. Inclusion of Additional Predictors: Although study specifically examined publication age and citation count, future research could explore the inclusion of other important variables (e.g., journal impact factor, author reputation, and open-access status) that could further improve models predicting citations. These factors have a profound impact on the discoverability of academic work. Cross-disciplinary Validation: The generalizability of the findings would benefit from the validation of the models across a wider selection of academic disciplines. Citation behavior across different fields can be different, and the inclusion of field-specific variables could improve the projection accuracy of citation trends. Machine Learning and Hybrid Models: With the advent of machine learning techniques, one possible direction is the development of hybrid models that integrate traditional statistical approaches (like the ARIMA and AHP methods used in this study) with more modern machine learning techniques (like neural networks or deep learning algorithms). These adaptations would enable more robust predictions through the modeling of complex nonlinear relationships within the datasets. Looking Through the Digital Lens: Considering that academic research communication is becoming more reliant on digital channels, it may also be useful to analyze how online visibility, social media activity, and digital repositories influence citation numbers. If we choose to consider these factors, our insights into how new media and digital tools affect the citation dynamics of academic publications may become more accurate and realistic. This study only focused on specific years of the relationship between publication age (time since publication) and citation count, but future studies can focus on the long-term temporal patterns and how the relationship between publication age and citation count changes over time. Understanding these emerging long-term trends may help us understand how academic research develops and positions itself progressively. Future research could help in bridging those gaps to produce improved models to predict academic impact and also contribute towards building better bibliometric analysis tools.

Reference

- [1]. G. C. Santos, F. Barboza, A. C. P. Veiga, and K. G. de Souza, "Portfolio Optimization using Artificial Intelligence: A Systematic Literature Review," Aug. 12, 2022, Universidade Nove de Julho. doi: 10.5585/exactaep.2022.21882.
- [2]. M. Mäntylä and V. Garousi, "Citations in Software Engineering -- Paper-related, Journal-related, and Author-related Factors," Jan. 01, 2019, Cornell University. doi: 10.48550/arXiv.1908.
- [3]. P. Breuer and J. P. Bowen, "Empirical Patterns in Google Scholar Citation Counts," p. 398, Apr. 2014, doi: 10.1109/sose.2014.55.
- [4]. G. Abramo, T. Cicero, and C. A. D'Angelo, "Revisiting size effects in higher education research productivity," Sep. 04, 2011, Springer Science+Business Media. doi: 10.1007/s10734-011-9471-6.
- [5]. J. Tu, A. Yasin, and N. S. Mansor, "Enhancing Efficiency and Accuracy of Optimization Techniques in Time Series Data Prediction Using Machine Learning: A Systematic Literature Review," Nov. 26, 2024. doi: 10.32996/jcsts.2024.6.5.11.
- [6]. X. Xu, L. Wang, and S. T. Newman, "Computer-aided process planning – A critical review of recent developments and future trends," *International Journal of Computer Integrated Manufacturing*, vol. 24, no. 1. Taylor & Francis, p. 1, Nov. 06, 2010. doi: 10.1080/0951192x.2010.518632.
- [7]. S. L. V. Papineni, S. Yarlagadda, H. Akkineni, and A. M. Reddy, "Big Data Analytics Applying the Fusion Approach of Multicriteria Decision Making with Deep Learning Algorithms," *International Journal of Engineering Trends and Technology*, vol. 69, no. 1, p. 24, Jan. 2021, doi: 10.14445/22315381/ijett-v69i1p204.
- [8]. P. Dhamija and S. Bag, "Role of artificial intelligence in operations environment: a review and bibliometric analysis," *The TQM Journal*, vol. 32, no. 4. Emerald Publishing Limited, p. 869, Mar. 06, 2020. doi: 10.1108/tqm-10-2019-0243.
- [9]. J. A. G. Moreira, X. H. T. Zeng, and L. A. N. Amaral, "The Distribution of the Asymptotic Number of Citations to Sets of Publications by a Researcher or from an Academic Department Are Consistent with a Discrete Lognormal Model," Nov. 16, 2015, Public Library of Science. doi: 10.1371/journal.pone.0143108.
- [10]. D. Wang, C. Song, and A. Barabási, "Quantifying Long-Term Scientific Impact," Oct. 03, 2013, American Association for the Advancement of Science. doi: 10.1126/science.1237825.
- [11]. J. R. Nash, R. J. Araújo, and G. S. Shideler, "Contributing factors to long-term citation count in marine and freshwater biology articles," Nov. 21, 2017, Wiley. doi: 10.1002/leap.1136.

- [12] .A. Martín-Martín, E. Orduña-Malea, J. M. Ayllón, and E. D. López-Cózar, “Reviving the past: the growth of citations to old documents,” arXiv (Cornell University), Jan. 2015, doi: 10.48550/arXiv.1501.
- [13] M. Wang, G. Yu, and D. Yu, “Effect of the age of papers on the preferential attachment in citation networks,” *Physica A Statistical Mechanics and its Applications*, vol. 388, no. 19, p. 4273, May 2009, doi: 10.1016/j.physa.2009.05.008.
- [14]. P. Lara-Benítez, M. Carranza-García, and J. C. Riquelme, “An Experimental Review on Deep Learning Architectures for Time Series Forecasting,” Nov. 24, 2020, World Scientific. doi: 10.1142/s0129065721300011.
- [15]. J. Zhang, “Forecast of Shanghai Port Throughput Based on ARIMA,” in *IOP Conference Series Earth and Environmental Science*, IOP Publishing, Aug. 2021, p. 12042. doi: 10.1088/1755-1315/831/1/012042.
- [16]. A. F. Raffee, H. A. Hamid, R. M. S. R. Mohamed, and M. I. Jaffar, “Time Series Analysis of PM10 Concentration in Parit Raja Residential Area,” *International Journal of Engineering & Technology*, vol. 7, p. 15, Aug. 2018, doi: 10.14419/ijet.v7i3.23.17252.
- [17]. Z. Jiaqian and Y. Diao, “Analysis on Evaluation Index System of Network Teaching Quality Based on Analytic Hierarchy Process,” *Learning & Education*, vol. 9, no. 2, p. 8, Nov. 2020, doi: 10.18282/l-e.v9i2.1386.
- [18]. A. Nesticò and P. Somma, “Comparative Analysis of Multi-Criteria Methods for the Enhancement of Historical Buildings,” *Sustainability*, vol. 11, no. 17, p. 4526, Aug. 2019, doi: 10.3390/su11174526.
- [19]. A. Ishizaka and A. Labib, “Analytic Hierarchy Process and Expert Choice: Benefits and limitations,” *OR Insight*, vol. 22, no. 4, p. 201, Oct. 2009, doi: 10.1057/ori.2009.10.
- [20]. J. Tu, A. Yasin, and N. S. Mansor, “Enhancing Efficiency and Accuracy of Optimization Techniques in Time Series Data Prediction Using Machine Learning: A Systematic Literature Review,” Nov. 26, 2024. doi: 10.32996/jcsts.2024.6.5.11.
- [21]. S. Wen, “Research on the Application of Artificial Intelligence Platform in Quantitative Investment,” Jul. 21, 2023. doi: 10.26855/acc.2023.06.009.
- [22] G. de Sá et al., “Analytic Hierarchy Process in Production Engineering: A Bibliometry Analysis,” *International Journal of Advanced Engineering Research and Science*, vol. 7, no. 7, p. 209, Jan. 2020, doi: 10.22161/ijaers.77.25.
- [23] .Dietrich, C. Decision making: Factors that influence decision making, heuristics used, and decision outcomes. *Inquiries Journal*(2010)., 2(02).

- [24]. Z. Ayağ and R. G. özdemidotr, “An analytic network process-based approach to concept evaluation in a new product development environment,” Jun. 01, 2007, Taylor & Francis. doi: 10.1080/09544820600752740.
- [25]. Y. Atikankul, “A Comparison of Statistical Methods for Forecasting the Price of Jasmine Rice,” *Applied Mechanics and Materials*, vol. 804, p. 304, Oct. 2015, doi: 10.4028/www.scientific.net/amm.804.304.
- [26]. Malsawmtluanga and Ch. Vabeihmo, “Assessment of Flood Hazard Zonation Using Geographic Information System and Analytical Hierarchy Process: A Case Study of Tlawng River Watershed in Sairang, Mizoram, India,” Mar. 06, 2022. doi: 10.46488/nept.2022.v21i01.011.
- [27]. W. Buczynski, F. Cuzzolin, and B. J. Sahakian, “A review of machine learning experiments in equity investment decision-making: why most published research findings do not live up to their promise in real life,” *International Journal of Data Science and Analytics*, vol. 11, no. 3. Springer International Publishing, p. 221, Apr. 01, 2021. doi: 10.1007/s41060-021-00245-5.
- [28]. F. Zong and L. Wang, “Evaluation of university scientific research ability based on the output of sci-tech papers: A D-AHP approach,” *PLoS ONE*, vol. 12, no. 2, Feb. 2017, doi: 10.1371/journal.pone.0171437.