A Study on BP Neural Network-Based Evaluation Method for Academic Discourse Power (Postprint)

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Abstract

[Purpose/Significance] Academic discourse power constitutes an integral component of China's international discourse power system and represents a primary manifestation of national soft power in political, economic, and scientific-technological domains. Analyzing evaluation methodologies for academic discourse power and comprehensively comparing the advantages, disadvantages, and stability of different approaches provides valuable references for the assessment of academic discourse power. [Method/Process] This study employs six weighting methods that do not require comprehensive evaluation values for single-model assessment, conducts fuzzy combination evaluation on results passing non-parametric tests to reduce single-evaluation bias and enhance evaluation credibility, and introduces BP neural networks to construct a neural network model based on gradient descent algorithms. [Results/Conclusion] We construct a three-dimensional evaluation system for academic discourse power encompassing academic leadership based on innovation leadership indices, academic influence based on citation analysis indicators, and academic dissemination power based on Altmetrics indicators. Fuzzy Borda evaluation can comprehensively consider both the evaluation values and relative ranking orders from single models, achieving internal combination of objective information and demonstrating higher accuracy compared to single evaluation models. Based on this, we construct an academic discourse power evaluation model that integrates BP neural networks.

Full Text

Exploring Evaluation Methods for Academic Discourse Power Integrated with BP Neural Network

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Abstract: [Purpose/Significance] Academic discourse power constitutes an integral component of China's international discourse power system and represents a primary manifestation of national political, economic, scientific, and technological soft power. Analyzing evaluation methods for academic discourse power and comprehensively comparing the advantages, disadvantages, and stability of different approaches provides valuable references for academic discourse power evaluation. [Method/Process] This study employs six weighting methods that do not require comprehensive evaluation values for single-model assessment, conducts fuzzy combination evaluation on results that pass non-parametric testing to reduce single-evaluation bias and enhance evaluation credibility, and introduces BP neural networks to construct a neural network model based on gradient descent algorithms. [Result/Conclusion] The research establishes a three-dimensional academic discourse power evaluation system comprising academic leadership based on innovation leadership indices, academic influence based on citation analysis metrics, and academic communication capacity based on Altmetrics indicators. Fuzzy Borda evaluation can comprehensively consider both the magnitude of evaluation values and the relative ranking order from single models, achieving internal combination of objective information with higher accuracy than single evaluation models. Based on this, an academic discourse power evaluation model integrated with BP neural networks is constructed.

Keywords: Academic Discourse Power; BP Neural Network; Evaluation Method; Objective Weighting; Fuzzy Combination Evaluation

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1. Literature Review

Academic discourse power represents a crucial component of national scientific and technological innovation, development, and soft power, reflecting a country's status and influence in the international academic discourse power structure. Current scholarly research on academic discourse power evaluation remains limited, with most studies concentrating on the connotation, manifestations, and existing problems of academic discourse power. Wang Xu notes that existing research on academic journal discourse power features more "ought-to-be" appeals than "as-is" analyses, lacking multi-dimensional integration and calling for multi-dimensional, multi-element, multi-indicator, and multi-method fusion for evaluating academic journal discourse power [1]. Shao Yafen examines academic discourse power from the perspectives of discourse disseminators (journal editorial boards) and discourse platforms (SSCI-indexed journals), demonstrating significant correlations between editorial board composition, university research output, and national international reputation [2]. Wang Xing quantitatively compares the distribution of academic discourse power by analyzing editorial boards of SCI journals in chemistry [3].

Due to the complexity of academic discourse power evaluation, which involves non-linear relationships rather than simple linear weighting, single evaluation indicators cannot comprehensively capture all relevant information. Limited perspectives may lead to biased results. Recognizing this, Yu Bo et al. employ Python and other analytical tools, integrating correlation analysis, principal component analysis, and regression analysis to quantitatively analyze and select evaluation indicators, constructing an evaluation index system for Chinese academic discourse power [4]. Wu Jian et al. divide evaluation indicators into academic productivity, influence, and leadership, analyzing how changes in cooperative network structures affect sports science discourse power from multidisciplinary perspectives [5]. Other scholars have proposed methodological innovations, such as Yan Yiwen et al., who develop a BP neural network-based evaluation method for government WeChat official account information dissemination effects [6], and Yu Liping, who proposes BP neural network-assisted non-linear evaluation methods while noting that neural network modeling should serve only as an auxiliary tool, with final selection still requiring comprehensive judgment based on evaluation purposes, logic, and actual indicator importance [7].

Although scholars have comprehensively interpreted discourse power from various levels and perspectives, research combining academic discourse power with academic journals and scientifically testing evaluation methods remains scarce. Current studies are predominantly qualitative, with limited empirical research. While existing evaluations addressing the three characteristics of discourse power offer reference value, they are not fully applicable. Most existing evaluation methods directly establish mathematical models using AHP, DEA, EWM, and other approaches, which struggle to eliminate randomness and subjectivity, potentially causing distorted results. The discourse power evaluation process involves numerous factors, and existing single evaluation methods cannot be directly applied. Therefore, this study uses 359 economics journals as empirical objects, proposes evaluation indicators for academic discourse power, conducts comprehensive selection following indicator selection principles, builds an evaluation index system, introduces membership degree and fuzzy frequency, employs fuzzy Borda method for combination evaluation, and constructs a BP neural network-based academic discourse power evaluation model.

2. Concepts and Theories

2.1 Academic Discourse Power

Academic discourse power refers to the ability of academic subjects possessing academic achievements or resources to influence and even lead the cognition and actions of other individuals through various discourse expressions [9]. Academic discourse power and academic organizations coexist symbiotically. When academic ideas generate influence, they inevitably become affiliated with certain academic organizations; conversely, perspectives without school support struggle to form influence. Moreover, the formation and development of academic discourse power is arduous, requiring overcoming questioning and comparison from other schools of thought, withstanding examination and criticism before gaining acceptance.

Sociologist Zheng Hangsheng views academic discourse power as the unity of "power" and "right," qualification and authority. "Right" discourse includes various forms such as unrestricted academic research autonomy, the right to assign fundamental meanings to supply and consumption, and rights to item recreation and innovation. "Power" discourse includes guidance of consciousness and behavior, critique of mainstream actions, and domination over individual actions [8].

Examining the formation process of academic discourse power reveals five constituent elements: discourse subject, content and carrier, communication media, discourse object, and implementation effects, corresponding to the three characteristics of discourse power: dissemination, guidance, and influence. Drawing upon Zhao Rongying et al.'s [9-10] definition of discourse power and the exposition in "Chinese Economics: Discourse Power, Paradigm Transformation, and Beyond" [11], this study defines the academic discourse power of academic journals—our empirical objects—as: the capacity of influential academic subjects, through dissemination on relevant research platforms, to lead academic research trends, influence academic research directions, and guide academic research innovation.

2.2 Related Theoretical Methods

Scientific evaluation is a dynamic, comprehensive, and collective concept. Broadly, it refers to the scientification of evaluation; narrowly, it refers to evaluation of scientific research activities. In the big data era, scientific evaluation has been applied to data research, primarily through quantitative analysis, qualitative analysis, and combined approaches. Citation analysis is a widely used method in academia, employed to study literature utilization patterns, scientific evaluation, forecasting, and relationships between science and society, revealing quantitative characteristics and internal laws through comparison, induction, abstraction, and generalization [13].

Compared with traditional citation metrics, Altmetrics represents a new approach to research dissemination, communication, and evaluation, essentially representing the deep integration of scientific evaluation's internal needs with social network applications, providing a newer, faster, and more comprehensive academic evaluation index system based on social network data [14].

Both traditional and alternative metrics require comprehensive evaluation methods in practice. Comprehensive evaluation theory encompasses statistics, sociology, operations research, and other disciplines, making the evaluation process complex. Single evaluation indicators cannot fully capture information. While multi-indicator comprehensive evaluation can assign evaluation indices using certain methods, the results remain abstract. Therefore, this study establishes combination evaluation based on single evaluation methods, considering biases in various weighting methods to effectively leverage their respective advantages.

Additionally, this study introduces the BP neural network model. Artificial neural networks have a history of over seventy years, with structures becoming increasingly complex and diverse as theoretical research deepens and technology advances. Currently, multi-layer feedforward networks are widely applied in BP neural network models, trained according to error backpropagation algorithms based on specific learning rules to reveal mapping relationships. The rationale for introducing BP neural networks lies in their ability to simulate relationships between indicators through forward and backward propagation of working signals and error signals, achieving evaluation of academic discourse power.

3. Academic Discourse Power Evaluation Integrating BP Neural Networks

3.1 Academic Discourse Power Evaluation Index System

Based on the definition of academic discourse power and synthesizing Zhao Rongying et al.'s [9-10] and Quan Heng's [11] expositions, this study divides the academic discourse power index system into three dimensions: academic leadership, academic influence, and academic communication capacity.

Academic leadership refers to the capacity to lead research frontiers, grasp academic development trends, occupy commanding heights in academic research, and drive academic innovation and leadership in academic exchanges. This study proposes an innovation leadership index to quantify academic leadership.

Academic influence refers to the academic impact generated by journals in the academic community, evaluating the depth and breadth of a journal's publications' influence on the academic field or discipline during a specific period. Traditional citation analysis has a long history with mature research methods and systems, and its results are widely recognized and considered reasonable for scientific evaluation.

Academic communication capacity refers to journals' dissemination ability in traditional media and new media contexts in the internet era. In the big data era, discourse power manifests more in how journals correctly guide users to like, comment, forward, adopt, include, and index academic information. These multimodal discourse behaviors can be captured by Altmetrics indicator data (including reading counts, citation counts, news mentions, etc., from mainstream media, social media, blogs, forums, and other platforms) [12]. The specific evaluation indicators are shown in .

** Academic Journal Discourse Power Evaluation Index System and Data Sources**

Discourse Power Dimension	Indicators	Data Sources
Academic Leadership	Innovation Leadership Index	Clarivate's 2020 Research Frontiers
Academic Influence	Total citations, Impact factor, 5-year impact factor, Cited impact factor, Immediacy index, Eigenfactor score, Article influence score, Total articles, Cited half-life, JIF average percentile, Citing half-life, CiteScore, SJR, SNIP, H5-index, H5-median	Web of Science Journal Citation Report, Google Scholar, Scopus

Discourse Power Dimension	Indicators	Data Sources
Academic Communication Capacity	Newsmentions, Blogmentions, Policymentions, Patentmentions, Twittermentions, Peerreviewmentions, Weibomentions, Facebookmentions, Wikipediamentions, Google+ mentions, LinkedInmentions, Reddit mentions, Pinterestmentions, F1000mentions, Q&Amentions, Videomentions, Syllabimmentions	Altmetric Explorer

3.2 Data Processing

The journals studied originate from 373 academic journals in the "Economics" category indexed by JCR. After removing journals with missing data or those not retrieved in Altmetric Explorer, 359 academic journals remained as the final research objects.

Raw indicator data underwent standardization processing, converted to unified dimensionless values using extremum normalization and mapped to the [0,1] range to obtain a normalized data matrix. Kolmogorov-Smirnov and Shapiro-Wilk tests were applied to indicator data, with Sig values all below 0.05, indicating significant differences. Correlation tests were conducted to screen and remove highly repetitive indicators, ensuring relative independence among dimensional evaluation indicators.

Based on the definition of academic discourse power, the evaluation index system was divided into three dimensions. For academic leadership, only the innovation leadership index was calculated without addition or deletion. The academic influence evaluation system removed seven indicators with correlation coefficients greater than 0.9: 5-year impact factor, immediacy index, Eigenfactor score, total articles, SNIP, article influence score, and H5-median. The academic communication capacity indicators showed no significant overlap in correlation analysis, though many zero values existed. Indicators with zero coverage rates—Weibomentions, LinkedInmentions, Pinterestmentions, F1000mentions, and Syllabimmentions—were removed, leaving 12 evaluation indicators in the academic communication capacity dimension.

3.3 Research Method Selection

Current weight determination methods for multiple evaluation indicators can be divided into two categories: individual or group-based subjective preferences and objective original data information-based methods. Among objective weighting methods, rough set and regression analysis methods require comprehensive evaluation opinions or values, while subjective weighting depends on expert or individual subjective opinions, significantly influenced by background environments and difficult to explain scientifically.

Applying different methods to evaluate the same journals often yields divergent results, with each method having distinct advantages and disadvantages. Relying on a single evaluation method presents clear limitations. This study does not employ expert subjective evaluation for three-dimensional indicator weighting, and the collected original data contain only attribute values without comprehensive evaluation values. Therefore, six objective methods not requiring pre-existing comprehensive values were adopted: factor analysis [18], principal component analysis [19], entropy method [20], coefficient of variation method [21], deviation maximization method [22], and grey relational analysis [23] for single-model evaluation. This approach reduces errors from single methods and establishes combination evaluation based on these methods to leverage their respective strengths, yielding more scientific, reasonable, and credible results.

After dimensionless processing of raw indicator data and uniform translation to eliminate zero-value effects, a weighted matrix was constructed. Non-parametric tests were conducted on single and combination model results. Based on consistent test results, weights were assigned, differences among various ranking results were comprehensively compared, membership degrees were introduced, fuzzy combination methods [24] were applied for combination evaluation, and a BP artificial neural network algorithm was integrated to construct the academic discourse power evaluation model.

3.4 Comparative Analysis of Evaluation Results

(1) Factor Analysis and Principal Component Analysis. Factor analysis yielded a first component eigenvalue of 5.620 and a second of 1.483, jointly explaining 78.931% of variance in international economics journals' original evaluation indicator data. Initial eigenvalues represent factor characteristic roots obtained during data analysis. Although only two factors were extracted after deleting redundant indicators for academic discourse power evaluation, the results remain valid.

During factor extraction, since some extracted components cannot strongly explain all indicator information, matrix rotation was performed to simplify the factor loading matrix structure. Using orthogonal rotation to maximize distances between column elements, the rotated component matrix yields greater loads for each evaluation indicator on respective principal components. Factor rotation was based on the first two common factors.

Interpretation and representativeness tests show that both methods aim to make extracted factors meaningful. Factor 1 covers 8 indicators, factor 2 covers 5 indicators. Principal component 1 has large loads on 11 indicators, and principal component 2 on 5 indicators. L.R. Fabrigar et al. [26] argue that extracted common factors must include at least 4 indicators to be considered valid; too few indicators lead to incomplete information or insufficient explanatory power. Therefore, both methods demonstrate good interpretability and representativeness.

Monotonicity tests were conducted using extracted factors/principal components as independent variables and final evaluation results as dependent variables in ridge regression (k=0.01). Ridge regression, an improvement on ordinary least squares, sacrifices unbiasedness and reduces precision for more realistic regression coefficients. Both methods yielded positive regression coefficients with high R^2 values, passing the monotonicity test.

(2) Entropy Method, Coefficient of Variation Method, Deviation Maximization Method, and Grey Relational Analysis. The entropy method compensates for principal component analysis' insufficient consideration of two relational variables. Based on each dimensional indicator's contribution to 359 economics journals, information entropy values, difference coefficients, and weights were calculated according to entropy principles, as shown in .

** Entropy Values, Information Utility Values, and Weight Coefficients for Evaluation Indicators**

Indicator	Entropy Value	Information Utility Value	Weight
Total Citations	0.9557	0.0443	0.029
Cited Half-life	0.9848	0.0152	0.088
Newsmentions	0.9705	0.0295	0.082
Blogmentions	0.9589	0.0411	0.057
CiteScore	0.7659	0.2341	0.058

Note: Limited to partial data due to space constraints.

The coefficient of variation method reflects the degree of variation in journals' indicator values. Standard deviation, mean, coefficient of variation, and weights were calculated. The deviation maximization approach calculates weights based on data information provided by original indicators but uses a uniform formula without highlighting indicator independence, potentially causing large final result differences and low compatibility. Therefore, this study introduces independent weights in deviation maximization, considering indicator independence and improving compatibility. Unlike other weighting methods that often assign greater weight to total citations or impact factors, this method gives maximum weight to citing half-life, followed by cited half-life.

In grey relational analysis, the reference value defaults to the maximum value of evaluation items. Correlation coefficients are calculated using the correlation formula, showing only the correlation between reference and comparison sequences. Total correlation degrees are obtained through weighted averaging.

(3) Fuzzy Borda Combination Evaluation. Single evaluation method results reveal varying preferences for evaluation indicators. For academic influence indicators, entropy weighting favors total citation frequency, while deviation maximization favors citing half-life. Each method's final evaluation values and relative ranking orders show significant inconsistency. Appropriate combination of single evaluation models can maximize useful information utilization and yield more reasonable results. Therefore, this study employs fuzzy Borda method for combination evaluation based on the six methods above.

Fuzzy Borda method comprehensively considers multiple evaluators' preference orders and utility values for multiple targets [27]. After confirming consistency among single evaluation results, fuzzy Borda combination evaluation was applied to six evaluation sets (weighting methods). Membership functions and fuzzy Borda numbers integrate differences in scores and rankings from different weighting methods. Based on fuzzy Borda calculation formulas [24], membership function values between methods were obtained, followed by membership superiority degrees, fuzzy frequencies, and fuzzy frequencies, yielding combination evaluation scores shown in .

** Kendall Test Statistics**

Kendall's W	Chi-square	Asymptotic Significance
0.914	183.725	0.000

The Kendall test shows an asymptotic significance of 0.000 (<0.05), indicating that the six weighting methods produce associated (consistent) results. Kendall's coefficient of concordance is 0.914 (>0.8), with a chi-square value of 183.725, demonstrating strong evaluation consistency.

** Comparison of Single and Combined Evaluation Model Results**

Journal	Factor Analysis	Principal Component	Entropy	Variation	Deviation	Grey Relational	Fuzzy Borda
Quarterly Journal of Economics	0.5644	0.5649	0.5697	0.5713	0.5652	0.5692	0.5674
Journal of Economic Perspectives	0.4325	0.4327	0.4341	0.4332	0.4322	0.4329	0.4329
Economic Geography	0.4628	0.4631	0.4639	0.4646	0.4631	0.4643	0.4637

Note: All evaluation model scores are normalized. See JCR for omitted journals.

Although the six methods show consistent results, combination models may produce random errors during final calculation, or inappropriate combination models could cause deviations despite method consistency. Therefore, post-hoc testing of the fuzzy Borda combination model is necessary, using rank correlation coefficients to ensure consistency between combination and single evaluation results. All inter-model correlation coefficients exceed 0.8, indicating strong result consistency.

Findings reveal that top-ranked journals excel in both traditional citation metrics and new media indicators under academic communication capacity, with higher mention counts in news and social media than other journals. These journals show small variance among indicators, indicating balanced development in expanding influence and adapting to the internet era. Overall, the United States dominates as an academic powerhouse, with absolute advantages in journal indexing by major databases and article volumes, largely operating under rules set by the U.S. Chinese domestic academic journals remain in an absolutely weak position regarding discourse power.

The comprehensive academic discourse power evaluation demonstrates that introducing membership degrees and fuzzy Borda numbers can integrate ranking and scoring differences across methods, balance result variations, fully utilize effective information, and overcome single-method limitations, yielding more reasonable results. The BP neural network model achieves preset precision, with high correlation between expected and actual training results, indicating applicability to real-world evaluation.

3.5 BP Neural Network Evaluation Model

(1) Model Construction. Standard BP neural networks have been widely applied across fields with mature learning algorithms and model functions, making them adaptable for academic discourse power evaluation. BP neural networks can avoid subjective human factors and, through training, discover intrinsic relationships between inputs and outputs, storing them as weights in the network. This enables personalized evaluation systems designed for different academic discourse power subjects, enhancing model adaptability and universality.

Considering single hidden layer approximation capability and network scale for academic discourse power evaluation, this study designed one hidden layer with screened secondary evaluation indicators from three dimensions as input layer nodes, output layer neuron count as evaluation result count. Since excessive or insufficient hidden layer nodes affect expected outcomes, the empirical formula and trial-and-error method were used to determine the specific number. The common empirical formula for hidden layer neuron count is:

$$M = \sqrt{m+n} + a$$

where n and m represent input and output neuron counts respectively, and a is a constant from 1 to 10. Using trial-and-error with 4-8 nodes for training, hidden layer nodes were determined based on maximum network mean square error during iteration. Using the Neural Network Toolbox, five BP neural networks were constructed. Combined with local minimum average error and Stack Overflow value ranges, hidden layer neurons were determined to be 5. The specific evaluation model is shown in [Figure 1: see original paper].

[Figure 1: see original paper] Neural Network Topology for Academic Discourse Power Evaluation Model

Since raw data underwent two-dimensional mapping processing, the hidden layer uses the tansig transfer function, the output layer uses logsig, the learning function is default learngdm, the training function is trainlm, and error training adopts the Levenberg-Marquardt method. MSE uses the default function:

$$MSE(y, y') = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2$$

where MSE represents the expected value of squared differences between true and predicted values, with larger values indicating poorer prediction effects. Input neurons number 22, output neurons number 1, and hidden neurons number 5. Specifying initial weights and thresholds would cause parameters and weights to correct in the same direction, so values between 0 and 1 were randomly selected. The BP neural network academic discourse power evaluation model training process is shown in [Figure 2: see original paper].

[Figure 2: see original paper] BP Neural Network Academic Discourse Power Evaluation Model Flow

For sample design, international economics journal data were randomly divided at an 8:2 ratio, with 80% as training set and 20% as test set. Considering parameters and datasets, the ideal situation of sufficiently small errors is difficult to achieve. Maximum iterations were set at 500 using a 22-5-1 single hidden layer BP network. Training data were input for learning, stopping when target error was reached. The resulting network weights and thresholds served as the optimal network pattern for academic journal discourse power evaluation, used to validate model feasibility. Training parameters were set as:

```
net.trainParam.show = 50
net.trainParam.lr = 0.01
net.trainParam.mc = 0.9
net.trainParam.epochs = 500
net.trainParam.goal = 0.0001
[net, tr] = train(net, P, T)
```

(2) Results Analysis. After initializing network parameters, training set data were input for training. With limited datasets and training iterations, model output values closely approximated expected values after reaching the target MSE. Training cycles stopped after achieving average error targets. With only one hidden layer, error values (default 0) reached 0.0001. The ideal optimal situation is often unattainable in practice, and excessively small errors may cause overfitting. The relationship between expected and actual output values in the training set is shown in [Figure 3: see original paper].

[Figure 3: see original paper] Comparison and Correlation Analysis Between Expected and Actual Output Values in Training Set

The figure reveals that the BP neural network-based academic discourse power evaluation model performs well on the training set, with a correlation coefficient R of 0.99996 between expected and actual output values.

Key findings include: First, the BP neural network algorithm can meet preset precision requirements through training set training, with prediction rates exceeding 80% based on gradient descent optimization algorithms, demonstrating feasibility for constructing academic discourse power evaluation models. Second, weights obtained through continuous self-learning in BP neural networks avoid subjective human weight assignment while reducing mutual interference between indicators. Test set error values demonstrate strong practicality of the journal academic discourse power evaluation model based on neural network algorithms. Finally, using a 22-5-1 single hidden layer BP network to achieve preset precision, trained weights map weight tendencies of employed evaluation methods to some extent. The BP artificial neural network based on gradient descent algorithms shows high correlation with fuzzy combination evaluation, indicating that trained neural network models can produce evaluation results for new input data.

Conclusion

This study proposes an academic discourse power evaluation model integrating BP neural network algorithms. Six single evaluation methods and fuzzy Borda combination evaluation were first applied to comprehensively evaluate economics journals' academic discourse power, revealing certain differences. All single objective weighting results passed non-parametric tests, demonstrating high consistency among the six methods. The fuzzy combination evaluation model comprehensively considered evaluation value magnitude and relative ranking order differences, balancing result variations and fully utilizing effective information to overcome single-method limitations, yielding more reasonable results. The introduced BP neural network model achieved preset error rates, with high correlation between expected and actual training results, indicating that the constructed academic discourse power evaluation model can be applied in practice. The combination evaluation approach can serve academic discourse power comprehensive evaluation and related evaluation problems, providing references for quantitative and comprehensive evaluation research.

The six objective weighting methods assigned different weights to evaluation indicators, each with certain limitations. Overall, sample data and problem domains directly affect attribute importance. The weight determination, comprehensive evaluation, and combination evaluation methods in this study rely entirely on information contained in the data itself, avoiding human interference. However, when evaluation indicators contain redundant information, fuzzy comprehensive evaluation requires combination with other methods, and membership function determination lacks systematic approaches. Compared with typical non-linear evaluations like communication effects, using BP neural networks' error correction and avoidance functions for academic discourse power evaluation effectiveness requires further exploration. Model performance directly relates to training samples, with sample size and input quality affecting results. Due to the implicit nature of BP evaluation models, output layer results and input layer indicators do not have simple linear relationships and cannot be interpreted as regression coefficients. Further research should examine neuron counts, node numbers, and function distribution densities.

Furthermore, while this study employs currently well-regarded indicators, subsequent research must address how to select appropriate, scientific, and correct journal indicators and establish comprehensive evaluation models. Only through continuous improvement of evaluation index systems and methods, avoiding subjective data collection, and ensuring scientific sampling can evaluations become more persuasive.

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Author Contributions

Zhao Rongying: Research conceptualization, framework design, and paper guidance;
Zhu Weijie: Data analysis, paper writing, and revision;
Zhang Zhaoyang: Data acquisition and processing;
Li Xinlai: Data analysis and paper revision.

Note: Figure translations are in progress. See original paper for figures.