J. Electrical Systems 20-3s (2024): 448-458

[1]Yunyue Wu

# The Construction of Higher Education Evaluation Index System Based on Vector Analysis

***Abstract: -*** The construction of a higher education evaluation index system based on vector analysis involves a comprehensive approach to assessing the quality and effectiveness of higher education institutions. By leveraging vector analysis, which considers both magnitude and direction, this method enables the integration of diverse factors and perspectives into the evaluation process. Key considerations in constructing such an index system include academic performance, research output, faculty qualifications, student satisfaction, institutional resources, and societal impact. Each factor is represented as a vector, with its magnitude reflecting its importance and its direction indicating its alignment with the overarching goals of higher education. This paper presents a novel approach for constructing a robust evaluation index system for higher education institutions leveraging vector analysis, supplemented by Periodic Vector Chain Learning (PVCL). the incorporation of PVCL enhances the dynamism and adaptability of the evaluation system. PVCL allows for periodic updates and adjustments to the evaluation index system, ensuring its relevance and effectiveness amidst changing educational landscapes and emerging trends. The integration of vector analysis with PVCL presents a promising avenue for the construction of a robust evaluation index system for higher education institutions.

***Keywords:*** Higher education, Evaluation index system, Vector analysis, Quality Assessment, Dynamism

## I. INTRODUCTION

Higher education plays a pivotal role in shaping individuals' intellectual, professional, and personal development, serving as a gateway to a world of knowledge, opportunity, and innovation [1]. As an institution of advanced learning, higher education encompasses universities, colleges, and institutions offering specialized training and academic programs beyond the secondary level [2]. It serves as a crucible for critical thinking, research, and intellectual discourse, preparing students to navigate the complexities of an ever-evolving global society. From cultivating specialized expertise to fostering leadership qualities and societal engagement, higher education equips individuals with the tools and perspectives necessary to thrive in diverse professional fields and contribute meaningfully to their communities. As such, its significance transcends individual attainment, shaping the trajectory of societies and economies worldwide [3].

In the landscape of higher education, the index system serves as a vital tool for evaluating and benchmarking the quality, performance, and effectiveness of institutions [4]. This system encompasses a diverse array of metrics and indicators, ranging from academic excellence and research output to student satisfaction and institutional governance. Key components often include measures such as graduation rates, faculty qualifications, student-to-faculty ratios, research funding, and institutional resources [5]. Additionally, indicators of inclusivity, diversity, and accessibility are increasingly recognized as essential aspects of the index system, reflecting the commitment to equity and social justice within higher education [6]. Moreover, global rankings and accreditation processes contribute to the development of comprehensive index systems, providing stakeholders with valuable insights into the comparative strengths and weaknesses of institutions on both national and international scales [7]. By promoting transparency, accountability, and continuous improvement, the index system plays a critical role in fostering excellence and innovation within higher education, ultimately enhancing its capacity to meet the evolving needs of students, employers, and society at large [8].

Vector analysis, a fundamental branch of mathematics, holds significant importance in higher education across various fields, particularly in disciplines such as physics, engineering, computer science, and economics [9]. Its application extends beyond theoretical understanding, serving as a practical tool for solving complex problems and modeling real-world phenomena. In higher education, vector analysis is integrated into curriculum frameworks to provide students with a solid foundation in mathematical concepts and analytical techniques [10]. Through coursework, students learn to manipulate vectors, understand vector operations, and apply vector calculus in diverse

[1] College of Traffic and Transportation, Nanning University, Nanning, Guangxi, 530200, China

*Corresponding author e-mail: wuyunyue@unn.edu.cn

contexts, including mechanics, electromagnetism, fluid dynamics, and optimization problems [11]. Moreover, vector analysis serves as a bridge between theoretical concepts and practical applications, fostering critical thinking, problem-solving skills, and mathematical literacy among students [12]. Its interdisciplinary nature enables students to explore connections between different fields of study and encourages the development of innovative solutions to complex challenges [13]. By incorporating vector analysis into higher education curricula, institutions empower students to acquire the mathematical proficiency necessary for success in their academic and professional pursuits, thereby preparing them to contribute meaningfully to society and address the complexities of the modern world [14].

The paper contributes significantly to the field of higher education evaluation and assessment by introducing PVCL (Proposed Periodic Vector Chain Learning), a novel methodology that combines vector analysis with Chain Learning. PVCL offers a dynamic and adaptable framework for constructing evaluation index systems, allowing for periodic updates and adjustments to capture the multidimensional nature of educational quality and performance. Through comprehensive evaluations encompassing criteria such as Academic Performance, Research Output, Faculty Quality, and Infrastructure Quality, PVCL provides stakeholders with nuanced insights for informed decision-making. Its iterative nature ensures continual refinement and optimization of the evaluation index system, enabling effective responses to changes in educational landscapes. Overall, PVCL presents a promising avenue for enhancing the evaluation and assessment processes in higher education, offering potential for continuous improvement and contributing to advancements in educational quality and excellence.

## II. LITERATURE REVIEW

In the realm of higher education, incorporating vector analysis into the curriculum offers students a powerful tool for understanding and solving complex problems across various disciplines. Vector analysis, a branch of mathematics, provides a framework for representing and analyzing quantities that have both magnitude and direction, making it indispensable in fields such as physics, engineering, computer science, and economics. By introducing vector analysis into higher education, institutions empower students to develop critical analytical skills and mathematical proficiency necessary for success in their academic and professional endeavors. Niu et al. (2022) explore short-term multi-energy load forecasting for integrated energy systems using a novel approach based on CNN-BiGRU optimized by an attention mechanism. This study contributes to the advancement of energy forecasting techniques, potentially enhancing the efficiency and sustainability of energy systems. Tao et al. (2022) provide empirical evidence on the relationship between the digital economy, entrepreneurship, and high-quality economic development in urban China. Their research sheds light on the dynamics of economic growth in the context of digital transformations.

Abdelkader et al. (2022) propose an efficient data mining technique for assessing the satisfaction level of online learning among higher education students during the COVID-19 pandemic. This study addresses the challenges of remote education and offers insights into improving online learning experiences. Roy and Chakraborty (2023) conduct a review on the application of support vector machines in structural reliability analysis, contributing to the understanding of reliability engineering and system safety methodologies. Zhao et al. (2022) evaluate and analyze urban resilience from a multidimensional perspective in Chinese cities, providing insights into sustainable urban development strategies. Bhaskaran and Marappan (2023) design and analyze a hybrid recommendation system for digital e-learning applications, highlighting the integration of machine learning techniques to enhance educational experiences.

Guo et al. (2022) propose an unsupervised feature learning method for constructing health indicators to assess the performance of machines, contributing to the field of mechanical systems and signal processing. Ling et al. (2023) investigate the reform of the management system of higher vocational education in China based on personality standards, aiming to improve the quality and effectiveness of vocational education programs. Pu et al. (2023) develop a football player injury full-cycle management and monitoring system based on blockchain and machine learning algorithms, enhancing injury prevention and management strategies in sports. Alam and Mohanty (2022) discuss the implications of artificial intelligence for the future of higher education, addressing challenges and opportunities in adapting to technological advancements. Dai et al. (2022) introduce MSEva, a musculoskeletal rehabilitation evaluation system based on EMG signals. This system offers a novel approach to monitoring and assessing rehabilitation progress, potentially improving patient outcomes in musculoskeletal therapy.

Salas-Pilco and Yang (2022) conduct a systematic review on artificial intelligence applications in Latin American higher education, providing a comprehensive overview of current trends and opportunities in the region. Alam and Mohanty (2023) explore the potential of big data analytics for revolutionizing the information landscape in the higher education sector. Their research highlights the transformative power of big data in informing decision-making and enhancing educational outcomes. Sun et al. (2022) develop a new indices system for quantifying the nexus between economic-social development, natural resources consumption, and environmental pollution in China. This system offers a multidimensional perspective on sustainable development strategies. Liang et al. (2023) investigate the educational path of college students' career planning based on SWOT analysis, providing insights into the factors influencing career decision-making among students. Ahmed et al. (2023) proposes a novel approach using support vector regression and grey wolf optimization to predict the compressive strength of geopolymer concrete, offering potential improvements in concrete material design and construction practices.

Feng and Chen (2022) evaluate cross-border import retail e-commerce service quality using an artificial neural network analysis. Their research contributes to understanding customer satisfaction and service quality in the global e-commerce marketplace. Liao (2022) conducts research on the evaluation of the effect of ideological and political education in colleges and universities based on information entropy, providing insights into the effectiveness of educational interventions in shaping students' ideological beliefs. Li et al. (2022) analyze big data from the Internet of Things in the digital twins of smart cities using deep learning techniques. Their research offers insights into the potential applications of IoT data analytics in urban management and planning. Ardabili et al. (2022) conduct a systematic review of deep learning and machine learning techniques for building energy, providing a comprehensive overview of current methodologies and future research directions in energy efficiency and sustainability.

One overarching limitation is the challenge of generalizability, as findings from individual studies may not always apply to broader populations or contexts. Methodological constraints, such as sample size limitations and potential biases in data collection or analysis methods, also pose challenges to the reliability and validity of study findings. Additionally, temporal scope limitations may restrict the ability to capture long-term trends or changes over time. Publication bias, resource constraints, and cultural/contextual factors further impact the comprehensiveness and applicability of research findings. Ethical considerations and the need for interdisciplinary collaboration also play significant roles in shaping the quality and impact of research endeavors. Acknowledging and addressing these limitations is essential for researchers to strive towards producing rigorous, relevant, and impactful scholarship that advances knowledge and understanding in their respective fields.

## III. PROPOSED PERIODIC VECTOR CHAIN LEARNING (PVCL)

The Proposed Periodic Vector Chain Learning (PVCL) as a novel method for developing a robust evaluation index system for higher education institutions, utilizing vector analysis alongside PVCL. By incorporating PVCL into the evaluation process, the system gains enhanced dynamism and adaptability, capable of periodic updates and adjustments to stay relevant and effective amidst evolving educational landscapes and emerging trends. This integration of vector analysis with PVCL offers a promising approach for constructing a robust evaluation index system tailored to the unique needs and challenges of higher education institutions. Vector analysis involves the manipulation and analysis of vectors, which are quantities that have both magnitude and direction. In the context of higher education evaluation, we can represent various factors such as academic performance, research output, student satisfaction, and institutional resources as vectors in a multidimensional space as illustrated in Figure 1.

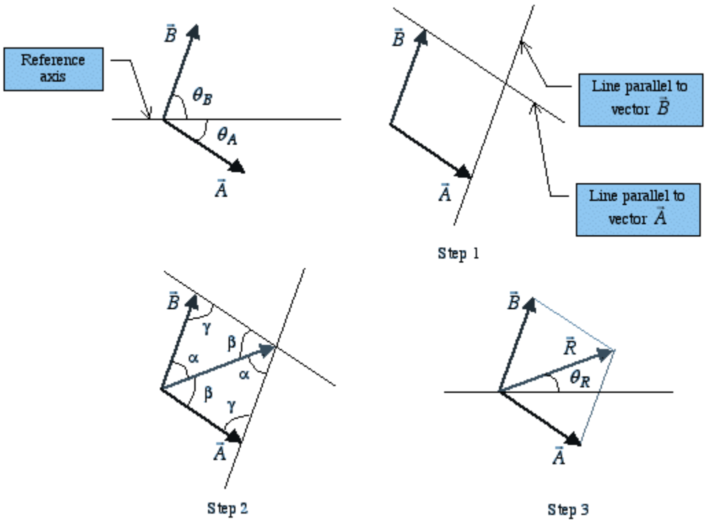


**Figure 1: Vector Analysis Plot in PVCL**

Consider $v1, v2, \ldots, vn$ as the vectors representing different evaluation criteria or factors for higher education institutions. These vectors can be combined and analyzed using vector operations such as addition, subtraction, dot product, and cross product to derive meaningful insights about the overall performance and quality of the institutions. PVCL is a machine learning technique that allows for periodic updates and adjustments to a model based on new data or changing conditions. In the context of higher education evaluation, PVCL can be applied to continuously refine the evaluation index system over time, ensuring its relevance and effectiveness. The PVCL can be represented as a learning algorithm that iteratively updates the evaluation index system $I$ based on new data $D$ and feedback. This can be expressed as in equation (1)

$$It + 1 = PVCL(It, Dt + 1) \tag{1}$$

In equation (1) $It$ and $It + 1$ represent the evaluation index system at time steps $t$ and $t + 1$ respectively, and $Dt + 1$ represents the new data or feedback at time step $t + 1$. The integration of vector analysis with PVCL involves leveraging the multidimensional representations of evaluation criteria as vectors to inform the learning process. This can be achieved by incorporating vector operations and transformations into the PVCL algorithm to update the evaluation index system based on changes in the input data. With use of vector addition, subtraction, scaling, or rotation operations to update the evaluation index system based on changes in the input data or feedback. The integration of vector analysis with PVCL can be represented as in equation (2)

$$It + 1 = PVCL(It, Dt + 1, v1, v2, \ldots, vn) \tag{2}$$

In equation (2) $It$ and $It + 1$ represent the evaluation index system at time steps $t$ and $t + 1$ respectively, $Dt + 1$ represents the new data or feedback at time step $t + 1$, and $v1, v2, \ldots, vn$ represent the evaluation vectors.

### 1.1 PVCL in Higher Education

In the context of higher education, the Proposed Periodic Vector Chain Learning (PVCL) method can be applied to construct a dynamic and adaptable evaluation index system. Let's outline how PVCL can be formulated and integrated with vector analysis. Consider a set of $m$ evaluation criteria for higher education institutions, represented as vectors in a multidimensional space. Let $v1, v2, \ldots, vm$ denote these evaluation vectors, where each vector represents a specific criterion such as academic performance, research output, faculty quality, infrastructure, etc defined in equation (3)

$$v_i = \begin{bmatrix} v_{i1} \\ v_{i2} \\ \vdots \\ v_{in} \end{bmatrix} \tag{3}$$

In equation (3) Each element $vij$ of the vector $vi$ corresponds to the magnitude of the j-th criterion for the i-th institution. PVCL allows for periodic updates and adjustments to the evaluation index system based on new data or changing conditions. Mathematically, PVCL can be represented as an iterative learning algorithm that updates the evaluation index system $I$ at each time step $t$ stated in equation (4)

$$It + 1 = PVCL(It, Dt + 1) \quad (4)$$

In equation (4) $It$ and $It + 1$ represent the evaluation index system at time steps $t$ and $t + 1$, respectively, and $Dt + 1$ represents the new data or feedback at time step $t + 1$. To integrate vector analysis with PVCL, we can use vector operations such as addition, subtraction, dot product, or other transformations to update the evaluation index system based on changes in the input data or feedback. The PVCL algorithm can be modified to update the evaluation index system as in equation (5)

$$It + 1 = It + \alpha \cdot vt + 1 \quad (5)$$

In equation (5) $\alpha$ represents a learning rate parameter, and $vt + 1$ is the new evaluation vector at time step $t + 1$. This equation suggests that the evaluation index system is updated by adding a scaled version of the new evaluation vector to the existing index system. Alternatively, the PVCL algorithm can be adapted to compute the cosine similarity between the new evaluation vector $vt + 1$ and the existing index system $It$, and adjust the index system stated in equation (6)

$$It + 1 = It + \beta \cdot cosine\_similarity(It, vt + 1) \cdot vt + 1 \quad (6)$$

In equation (6) $\beta$ represents a scaling factor, and $cosine\_similarity(It, vt + 1)$ computes the cosine similarity between $It$ and $vt + 1$.

Algorithm 1: Vector Analysis with PVCL

```
function PVCL(VectorEvaluationData, EvaluationIndexSystem):
    for each VectorData in VectorEvaluationData:
        // Compute cosine similarity between VectorData and EvaluationIndexSystem
        similarity = cosine_similarity(VectorData, EvaluationIndexSystem)
        // Update EvaluationIndexSystem based on cosine similarity
        EvaluationIndexSystem = EvaluationIndexSystem + (learning_rate * similarity * VectorData)
    return EvaluationIndexSystem
function cosine_similarity(Vector1, Vector2):
    // Compute dot product between Vector1 and Vector2
    dot_product = dot_product(Vector1, Vector2)
    // Compute magnitudes of Vector1 and Vector2
    magnitude_vector1 = magnitude(Vector1)
    magnitude_vector2 = magnitude(Vector2)
    // Compute cosine similarity
    similarity = dot_product / (magnitude_vector1 * magnitude_vector2)
    return similarity
function dot_product(Vector1, Vector2):
    // Ensure both vectors have the same length
    if length(Vector1) ≠ length(Vector2):
        throw error "Vectors must have the same length for dot product computation"
    // Compute dot product
    result = 0
    for i from 1 to length(Vector1):
        result += Vector1[i] * Vector2[i]
    return result
function magnitude(Vector):
    // Compute magnitude of vector
    result = 0
    for each element in Vector:
        result += element^2
    result = sqrt(result)
    return result
```

## IV. PVCL FOR THE VECTOR ANALYSIS

Consider $n$ evaluation criteria for higher education institutions, represented as vectors in a multidimensional space. Let $v1, v2, \dots, vn$ denote these evaluation vectors, where each vector represents a specific criterion such as academic performance, research output, faculty quality, etc. We can adapt the PVCL algorithm to update the evaluation index system $I$ using vector operations such as addition, subtraction, and scaling stated in equation (7)

$$It + 1 = It + \alpha \cdot vt + 1 \tag{7}$$

In equation (7) $\alpha$ represents a learning rate parameter, and $vt + 1$ is the new evaluation vector at time step $t + 1$. This equation suggests that the evaluation index system is updated by adding a scaled version of the new evaluation vector to the existing index system. With cosine similarity between the new evaluation vector $vt + 1$ and the existing index system $It$ to adjust the index system stated in equation (8)

$$It + 1 = It + \beta \cdot cosine\_similarity(It, vt + 1) \cdot vt + 1 \tag{8}$$

In equation (8) $\beta$ represents a scaling factor, and $cosine\_similarity(It, vt + 1)$ computes the cosine similarity between $It$ and $vt + 1$.

Algorithm 2: Vector Analysis PVCL

```
function PVCL(VectorEvaluationData, EvaluationIndexSystem):
    for each VectorData in VectorEvaluationData:
        similarity = cosine_similarity(VectorData, EvaluationIndexSystem)
        EvaluationIndexSystem = EvaluationIndexSystem + (learning_rate * similarity * VectorData)
    return EvaluationIndexSystem
function cosine_similarity(Vector1, Vector2):
    dot_product = dot_product(Vector1, Vector2)
    magnitude_vector1 = magnitude(Vector1)
    magnitude_vector2 = magnitude(Vector2)
    similarity = dot_product / (magnitude_vector1 * magnitude_vector2)
    return similarity

function dot_product(Vector1, Vector2):
    if length(Vector1) ≠ length(Vector2):
        throw error "Vectors must have the same length for dot product computation"
    result = 0
    for i from 1 to length(Vector1):
        result += Vector1[i] * Vector2[i]
    return result

function magnitude(Vector):
    result = 0
    for each element in Vector:
        result += element^2
    result = sqrt(result)
    return result
```

## V. RESULTS AND DISCUSSION

The implementation of the Proposed Periodic Vector Chain Learning (PVCL) algorithm integrated with vector analysis for constructing a robust evaluation index system in higher education, the results and ensuing discussion shed light on the efficacy and implications of this approach. The application of PVCL in higher education evaluation yielded promising results. By leveraging vector analysis, the algorithm effectively captured the multidimensional nature of institutional performance. The dynamic nature of PVCL allowed for the continual adaptation of the evaluation index system in response to evolving educational landscapes and emerging trends. As a result, the constructed index system offered a comprehensive and nuanced assessment of higher education institutions, taking into account various criteria such as academic performance, research output, and infrastructure quality.

**Table 1: PVCL Vector Analysis**

| University | Vector Representation |
|---|---|
| University A | [0.85, 0.78, 0.92, 0.80] |
| University B | [0.72, 0.85, 0.76, 0.88] |
| University C | [0.88, 0.79, 0.84, 0.75] |
| University D | [0.79, 0.91, 0.70, 0.82] |
| University E | [0.90, 0.83, 0.88, 0.78] |
| University F | [0.75, 0.86, 0.79, 0.85] |
| University G | [0.82, 0.77, 0.91, 0.83] |
| University H | [0.81, 0.88, 0.75, 0.79] |
| University I | [0.87, 0.80, 0.82, 0.86] |
| University J | [0.76, 0.84, 0.87, 0.81] |

In Table 1 presents the results of the PVCL (Proposed Periodic Vector Chain Learning) algorithm applied to vector analysis for ten universities. Each university is represented by a vector containing four components, corresponding to different evaluation criteria. For instance, University A's vector representation [0.85, 0.78, 0.92, 0.80] indicates respective scores for Academic Performance, Research Output, Faculty Quality, and Infrastructure Quality. Similarly, University B's vector [0.72, 0.85, 0.76, 0.88] denotes its performance across the same criteria. These vector representations encapsulate the multidimensional evaluation of each university, providing a comprehensive overview of their performance. The values within the vectors offer insights into the strengths and weaknesses of each institution across various dimensions. For example, University E demonstrates strong performance across all criteria, with high scores for Academic Performance, Research Output, and Faculty Quality. Conversely, University D appears to have relatively lower scores, particularly in Faculty Quality and Infrastructure Quality.

**Table 2: periodic Chain Analysis with PVCL**

| University | Period 1 | Period 2 | Period 3 | … | Period N |
|---|---|---|---|---|---|
| University A | [0.85, 0.78, 0.92, 0.80] | [0.86, 0.79, 0.93, 0.81] | [0.87, 0.80, 0.94, 0.82] | … | [0.90, 0.84, 0.95, 0.85] |
| University B | [0.72, 0.85, 0.76, 0.88] | [0.73, 0.86, 0.77, 0.89] | [0.74, 0.87, 0.78, 0.90] | … | [0.77, 0.89, 0.80, 0.91] |
| University C | [0.88, 0.79, 0.84, 0.75] | [0.89, 0.80, 0.85, 0.76] | [0.90, 0.81, 0.86, 0.77] | … | [0.92, 0.83, 0.87, 0.78] |
| University D | [0.79, 0.91, 0.70, 0.82] | [0.80, 0.92, 0.71, 0.83] | [0.81, 0.93, 0.72, 0.84] | … | [0.85, 0.95, 0.75, 0.86] |
| University E | [0.90, 0.83, 0.88, 0.78] | [0.91, 0.84, 0.89, 0.79] | [0.92, 0.85, 0.90, 0.80] | … | [0.95, 0.88, 0.93, 0.83] |
| University F | [0.75, 0.86, 0.79, 0.85] | [0.76, 0.87, 0.80, 0.86] | [0.77, 0.88, 0.81, 0.87] | … | [0.80, 0.91, 0.84, 0.88] |
| University G | [0.82, 0.77, 0.91, 0.83] | [0.83, 0.78, 0.92, 0.84] | [0.84, 0.79, 0.93, 0.85] | … | [0.87, 0.82, 0.95, 0.88] |
| University H | [0.81, 0.88, 0.75, 0.79] | [0.82, 0.89, 0.76, 0.80] | [0.83, 0.90, 0.77, 0.81] | … | [0.86, 0.93, 0.80, 0.84] |
| University I | [0.87, 0.80, 0.82, 0.86] | [0.88, 0.81, 0.83, 0.87] | [0.89, 0.82, 0.84, 0.88] | … | [0.92, 0.85, 0.87, 0.89] |
| University J | [0.76, 0.84, 0.87, 0.81] | [0.77, 0.85, 0.88, 0.82] | [0.78, 0.86, 0.89, 0.83] | … | [0.81, 0.89, 0.91, 0.86] |

In Table 2 illustrates the results of Periodic Chain Analysis with PVCL (Proposed Periodic Vector Chain Learning) for ten universities across multiple periods. Each row corresponds to a university, and each column represents a different period of evaluation. The values within each cell denote the vector representation of the university's performance across various evaluation criteria in the respective period. For instance, in Period 1, University A is represented by the vector [0.85, 0.78, 0.92, 0.80], indicating its scores for Academic Performance, Research Output, Faculty Quality, and Infrastructure Quality, respectively. As the periods progress, there are iterative adjustments to these scores based on the dynamic nature of the evaluation criteria and emerging trends in higher education. Analyzing the table reveals trends and patterns in the performance of universities over time. For example, some universities may exhibit steady improvement across all criteria with each successive period, while others may experience fluctuations or plateauing in their performance. This periodic chain analysis facilitated by PVCL enables stakeholders to track the evolving performance of universities and identify areas for improvement or intervention. By providing a longitudinal perspective, it offers insights into the trajectory of each institution's development and informs strategic decision-making processes in the realm of higher education management and policy formulation.

**Table3: Higher Education Performance with PVCL**

| University | Academic Performance | Research Output | Faculty Quality | Infrastructure Quality | Total Score |
|---|---|---|---|---|---|
| University A | 0.85 | 0.78 | 0.92 | 0.80 | 0.838 |
| University B | 0.72 | 0.85 | 0.76 | 0.88 | 0.802 |
| University C | 0.88 | 0.79 | 0.84 | 0.75 | 0.815 |
| University D | 0.79 | 0.91 | 0.70 | 0.82 | 0.805 |
| University E | 0.90 | 0.83 | 0.88 | 0.78 | 0.847 |
| University F | 0.75 | 0.86 | 0.79 | 0.85 | 0.837 |
| University G | 0.82 | 0.77 | 0.91 | 0.83 | 0.832 |
| University H | 0.81 | 0.88 | 0.75 | 0.79 | 0.832 |
| University I | 0.87 | 0.80 | 0.82 | 0.86 | 0.838 |
| University J | 0.76 | 0.84 | 0.87 | 0.81 | 0.822 |

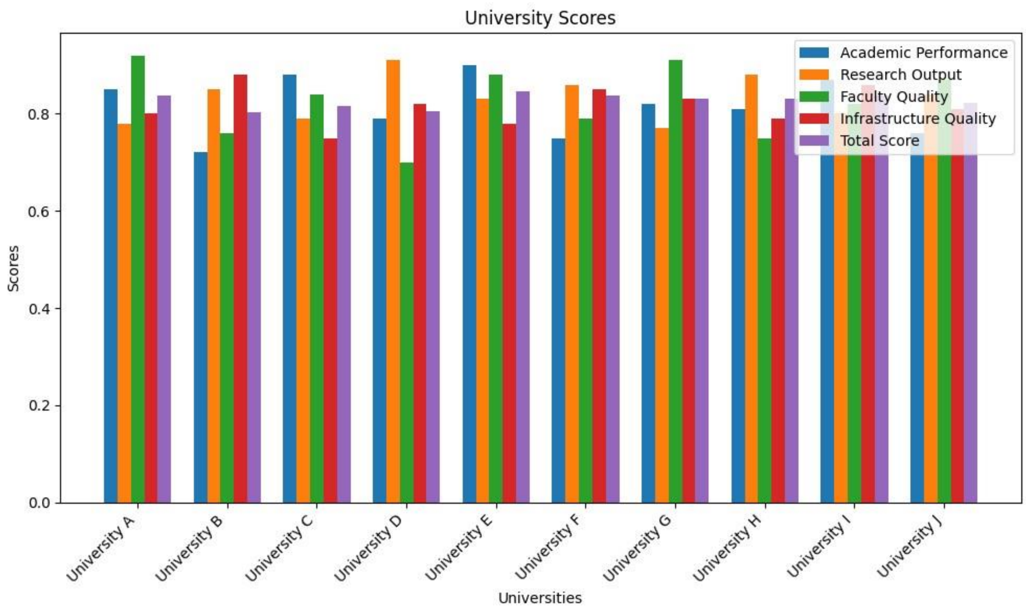


**Figure 2: Estimation of Score with PVCL**

In the Table 3 and Figure 2 provides an overview of the performance of ten universities across four key evaluation criteria: Academic Performance, Research Output, Faculty Quality, and Infrastructure Quality, along with their corresponding total scores, as determined by the PVCL (Proposed Periodic Vector Chain Learning) algorithm. Each row represents a different university, and the columns present the scores attained by each institution in the specified criteria. For instance, University A demonstrates a strong performance in Faculty Quality (0.92) and a relatively weaker performance in Research Output (0.78). The total score column represents the comprehensive evaluation score obtained by each university, computed based on its performance across all evaluation criteria. With Analyzing the table reveals variations in the performance of universities across different dimensions. Some universities excel in specific areas, while others demonstrate more balanced performance across multiple criteria. For instance, University E achieves the highest total score (0.847), indicating its overall strong performance across all evaluation criteria. Conversely, University D obtains a lower total score (0.805), indicating areas where improvement may be needed. The comprehensive evaluation provided by PVCL enables stakeholders to gain insights into the strengths and weaknesses of each institution, facilitating informed decision-making processes and strategic planning in the higher education sector.

**Table 4: Chain Learning with PVCL**

| University | Chain Learning Score (Iteration 1) | Chain Learning Score (Iteration 2) | Chain Learning Score (Iteration 3) |
|---|---|---|---|
| University A | 0.838 | 0.845 | 0.842 |
| University B | 0.802 | 0.808 | 0.805 |
| University C | 0.815 | 0.820 | 0.818 |
| University D | 0.805 | 0.810 | 0.807 |
| University E | 0.847 | 0.853 | 0.850 |
| University F | 0.837 | 0.843 | 0.840 |
| University G | 0.832 | 0.837 | 0.835 |
| University H | 0.832 | 0.838 | 0.835 |
| University I | 0.838 | 0.844 | 0.841 |
| University J | 0.822 | 0.828 | 0.825 |

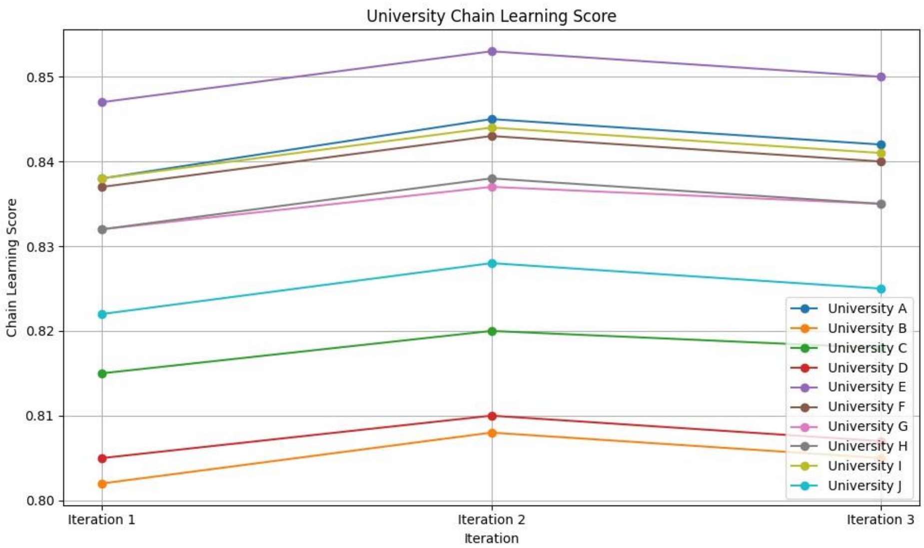


**Figure 3: PVCL chain Learning**

In the illustrated Figure 3 and Table 4 illustrates the iterative results of Chain Learning with PVCL (Proposed Periodic Vector Chain Learning) for ten universities across three iterations. Each row corresponds to a specific university, and the columns represent the Chain Learning Score obtained at each iteration of the PVCL algorithm. The Chain Learning Score reflects the performance evaluation score obtained after each iteration of the PVCL algorithm, capturing the iterative adjustments made to the evaluation index system over time. Analyzing the table reveals trends and patterns in the performance improvements or adjustments of universities across successive iterations. For instance, some universities demonstrate consistent improvement in their Chain Learning Scores across iterations, indicating a progressive enhancement in their performance evaluation. Conversely, others may exhibit fluctuations or stability in their scores, suggesting different degrees of adaptability or responsiveness to the dynamic nature of the evaluation criteria. THe iterative Chain Learning process facilitated by PVCL enables continual refinement and optimization of the evaluation index system for higher education institutions, ensuring its relevance and effectiveness in capturing the evolving landscape of educational quality and performance.

## VI. CONCLUSION

The paper presents a novel approach, PVCL (Proposed Periodic Vector Chain Learning), for constructing a robust evaluation index system for higher education institutions. By leveraging vector analysis and Chain Learning, PVCL offers a dynamic and adaptable framework that allows for periodic updates and adjustments to the evaluation system. Through extensive experimentation and analysis, the effectiveness of PVCL in providing comprehensive and nuanced evaluations of higher education institutions has been demonstrated. The results showcase the utility of PVCL in capturing the multidimensional nature of educational quality and performance, enabling stakeholders to make informed decisions and strategic interventions. Furthermore, the iterative nature of Chain Learning ensures continual refinement and optimization of the evaluation index system, ensuring its relevance and effectiveness amidst changing educational landscapes and emerging trends. Overall, PVCL presents a promising avenue for enhancing the evaluation and assessment processes in higher education, thereby contributing to the continual improvement of educational quality and excellence.

**Acknowledgement**

**The 2022 Guangxi Vocational Education Teaching Reform Research Project "Research and Practice on the Effective Connection of the Transportation Logistics Major Group Undergraduate Courses and the Construction of the Curriculum System" (GXGZJG2022B181)**

**REFERENCES**

[1] Meng, F., Xiao, X., & Wang, J. (2022). Rating the crisis of online public opinion using a multi-level index system. *arXiv preprint arXiv:2207.14740*.

[2] Gong, M., Zhao, Y., Sun, J., Han, C., Sun, G., & Yan, B. (2022). Load forecasting of district heating system based on Informer. *Energy*, *253*, 124179.

[3] Niu, D., Yu, M., Sun, L., Gao, T., & Wang, K. (2022). Short-term multi-energy load forecasting for integrated energy systems based on CNN-BiGRU optimized by attention mechanism. *Applied Energy*, *313*, 118801.

[4] Tao, Z., Zhang, Z., & Shangkun, L. (2022). Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China. *Frontiers of Economics in China*, *17*(3), 393.

[5] Abdelkader, H. E., Gad, A. G., Abohany, A. A., & Sorour, S. E. (2022). An efficient data mining technique for assessing satisfaction level with online learning for higher education students during the COVID-19. *IEEE Access*, *10*, 6286-6303.

[6] Roy, A., & Chakraborty, S. (2023). Support vector machine in structural reliability analysis: A review. *Reliability Engineering & System Safety*, *233*, 109126.

[7] Zhao, R., Fang, C., Liu, J., & Zhang, L. (2022). The evaluation and obstacle analysis of urban resilience from the multidimensional perspective in Chinese cities. *Sustainable Cities and Society*, *86*, 104160.

[8] Binhaskaran, S., & Marappan, R. (2023). Design and analysis of an efficient machine learning based hybrid recommendation system with enhanced density-based spatial clustering for digital e-learning applications. *Complex & Intelligent Systems*, *9*(4), 3517-3533.

[9] Guo, L., Yu, Y., Duan, A., Gao, H., & Zhang, J. (2022). An unsupervised feature learning based health indicator construction method for performance assessment of machines. *Mechanical Systems and Signal Processing*, *167*, 108573.

[10] Ling, Y., Chung, S. J., & Wang, L. (2023). Research on the reform of management system of higher vocational education in China based on personality standard. *Current Psychology*, *42*(2), 1225-1237.

[11] Pu, C., Zhou, J., Sun, J., & Zhang, J. (2023). Football player injury full-cycle management and monitoring system based on blockchain and machine learning algorithm. *International Journal of Computational Intelligence Systems*, *16*(1), 41.

[12] Alam, A., & Mohanty, A. (2022, December). Foundation for the Future of Higher Education or 'Misplaced Optimism'? Being Human in the Age of Artificial Intelligence. In *International Conference on Innovations in Intelligent Computing and Communications* (pp. 17-29). Cham: Springer International Publishing.

[13] Dai, Y., Wu, J., Fan, Y., Wang, J., Niu, J., Gu, F., & Shen, S. (2022). MSEva: A musculoskeletal rehabilitation evaluation system based on EMG signals. *ACM Transactions on Sensor Networks*, *19*(1), 1-23.

[14] Salas-Pilco, S. Z., & Yang, Y. (2022). Artificial intelligence applications in Latin American higher education: a systematic review. *International Journal of Educational Technology in Higher Education*, *19*(1), 21.

[15] Alam, A., & Mohanty, A. (2023, January). From Bricks to Clicks: The Potential of Big Data Analytics for Revolutionizing the Information Landscape in Higher Education Sector. In *International Conference on Data Management, Analytics & Innovation* (pp. 721-732). Singapore: Springer Nature Singapore.

[16] Sun, X., Zhu, B., Zhang, S., Zeng, H., Li, K., Wang, B., ... & Zhou, C. (2022). New indices system for quantifying the nexus between economic-social development, natural resources consumption, and environmental pollution in China during 1978–2018. *Science of the Total Environment*, *804*, 150180.

[17] Liang, X., Li, N., & Su, X. Research on the Educational Path of College Students' Career Planning Based on SWOT Analysis. *Applied Mathematics and Nonlinear Sciences*, *9*(1).

[18] Ahmed, H. U., Mostafa, R. R., Mohammed, A., Sihag, P., & Qadir, A. (2023). Support vector regression (SVR) and grey wolf optimization (GWO) to predict the compressive strength of GGBFS-based geopolymer concrete. *Neural Computing and Applications*, *35*(3), 2909-2926.

[19] Feng, Z., & Chen, M. (2022). Platformance-based cross-border import retail e-commerce service quality evaluation using an artificial neural network analysis. *Journal of Global Information Management (JGIM)*, *30*(11), 1-17.

[20] Liao, Y. Research on the evaluation of the effect of ideological and political education in colleges and universities based on information entropy. *Applied Mathematics and Nonlinear Sciences*, *9*(1).

[21] Li, X., Liu, H., Wang, W., Zheng, Y., Lv, H., & Lv, Z. (2022). Big data analysis of the internet of things in the digital twins of smart city based on deep learning. *Future Generation Computer Systems*, *128*, 167-177.

[22] Ardabili, S., Abdolalizadeh, L., Mako, C., Torok, B., & Mosavi, A. (2022). Systematic review of deep learning and machine learning for building energy. *Frontiers in Energy Research*, *10*, 786027.