Incorporating Intelligence in Multiple-Attribute Decision-Making using Algorithmic Framework and Double-Valued Neutrosophic Sets: Varied Applications to Employment Quality Evaluation for University Graduates

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Abstract: The evaluation of university employment quality is a comprehensive assessment of graduates' employment status and its alignment with market demands. This evaluation typically includes indicators such as employment rate, the relevance of job positions to majors, salary levels, job stability, and job satisfaction. By analyzing this data, universities can understand how graduates perform in the job market, assess the effectiveness of talent cultivation, and provide reference points for optimizing curriculum design, teaching methods, and industry-education integration. The employment quality evaluation for university graduates a MADM. Currently, Logarithmic TODIM (LogTODIM) and GRA techniques are employed to address MADM challenges. To handle uncertain data in this evaluation, the double-valued neutrosophic sets (DVNSs) have been introduced. This study constructs the double-valued neutrosophic number Logarithmic TODIM-GRA (DVNN-LogTODIM-GRA) technique to manage the MADM problem under DVNSs. To validate the proposed technique, a numerical study is conducted focusing on the employment quality evaluation for university graduates. The main contributions of this study are constructed: (1) The use of entropy to determine weight values under DVNSs; (2) The application of the DVNN-LogTODIM-GRA technique to effectively manage MADM; (3) The verification of the DVNN-LogTODIM-GRA technique through a numerical example related to the employment quality evaluation for university graduates.

Keywords: Multiple Attributes; Neutrosophic Sets; Decision Making; TODIM.

1. Introduction

According to statistics from the Ministry of Education, the number of university graduates nationwide in 2024 will reach 11.79 million, an increase of 210,000 compared to the previous year. In the context of a rapidly growing number of university graduates and a job market where the demand for talent significantly lags behind supply, the employment situation is becoming increasingly severe, with structural employment conflicts among university graduates becoming more prominent. The coexistence of "difficulty in finding jobs" and "difficulty in hiring" remains persistent in the job market. As the main institutions responsible for talent cultivation, universities—especially "comprehensive applied universities"—should, while adhering to their functional positioning and pursuing distinctive development, place greater emphasis on "serving local economic and social development" as a key pillar for continuously improving their talent cultivation programs. This will help align university talent training more closely with market demands and enhance job-person fit. Therefore, exploring the construction of a graduate employment quality evaluation system that aligns with the needs of local economic development is crucial. This system should evaluate employment quality from both the perspectives of graduates and employers, with a focus on the alignment between university talent cultivation objectives and the needs of national and local economic development sectors. This is not only in response to the need presented in the General Plan for Deepening the Reform of Educational Evaluation in the New Era issued by the Central Committee of the Communist Party of China and the State Council, which calls for continuous improvement of university evaluation systems but also serves to strengthen the interaction between higher education and social development. Furthermore, it enhances the performance of universities in their development, meets the need for talent cultivation to align with local economic development, and fosters mutual empowerment and harmonious growth between universities and society. In recent years, the evaluation of university graduate employment quality has been a focal point of academic research. With the rapid development of the economy, scholars have gradually deepened their exploration in this field. Ma [1] was among the first to reflect on the existing university graduate employment quality evaluation system, analyzing its shortcomings and proposing strategies for improvement, aiming to ensure that the evaluation system could achieve its intended outcomes 101010. Following this, Chen [2] analyzed the current state of university student employment quality evaluation and emphasized the necessity of constructing an evaluation index system, while also providing specific application suggestions. In 2019, Qi and Cheng [3] summarized relevant literature and practical experience in employment guidance, categorizing employment quality into three dimensions: graduate satisfaction, social evaluation satisfaction, and employer satisfaction. They used the Delphi method and the Analytic Hierarchy Process (AHP) to construct a systematic evaluation framework. Wei [4] integrated big data mining technology into the employment quality evaluation model, addressing the low reliability of traditional models. By introducing big data, this model was able to capture employment trends more effectively and improve the scientific rigor of the evaluation results. In the same year, Yang, Qiu, and Guo [5] conducted a systematic review of employment quality evaluation research over the past decade, pointing out the lack of quantitative analysis in existing studies and suggesting that future research should focus on enhancing data collection and analysis for employment tracking. Gu and Lin [6] further explored how to construct a scientific and reasonable university graduate employment quality evaluation system. They proposed that graduate employment quality involves not only employment rates but also multiple dimensions such as university positioning and discipline construction. Liang, Zhang, and Liang [7] focused on industry-specific universities and analyzed the factors affecting employment quality from the perspectives of graduates, universities, employers, and society. They constructed a multi-layered employment quality evaluation system and refined the fuzzy comprehensive evaluation model using AHP and expert scoring. Cao and Yi [8] concentrated on graduates in Hunan province and developed a more comprehensive employment quality evaluation index system. This system integrated domestic and international research findings and determined indicator weights using AHP, covering five dimensions: government, universities, employers, society, and students. Zhang, Li and Ye [9] introduced the CIPP model in their study, using the four dimensions of "context, input, process, and product" to construct a university graduate employment quality evaluation system. They applied AHP to determine indicator weights and validated the system's feasibility. The most recent study by Yan, Pei and Li [10] approached the evaluation from the perspective of universities serving local economic development. Based on higher education political theory, this study constructed a more focused and quantifiable employment quality evaluation system and provided targeted suggestions to promote positive cycles between talent cultivation and industrial demand.

MADM is a significant area of research in management science [11-15]. It finds wide applications in real-life scenarios such as investment project decision evaluation, supplier selection analysis, and location site selection [16-20]. MADM can be divided into two key parts: the expression of expert decision-making opinions and the selection of alternative solutions [21-25]. In the first part, the complexity of external factors and human-bounded rationality often leads to fuzzy decision-making outcomes [26-29]. To address this, scholars commonly employ fuzzy sets to gather expert evaluations. In the second part, the method of comparing and ranking schemes is typically used to identify the optimal solution [30-35]. The employment quality evaluation for university graduates falls under the category of MADM. To tackle MADM challenges in this context, researchers have recently utilized the LogTODIM [36] and GRA techniques [37]. Additionally, the DVNSs [38] have been proposed to characterize uncertain data during the evaluation process. In this study, we employ the DVNN-LogTODIM-GRA technique to address MADM with DVNSs. To validate the proposed technique, a numerical study is conducted, focusing on the employment quality evaluation for university graduates. The key goals and motivations of this study are constructed: (1) Utilizing the entropy to determine weight values under DVNSs; (2) Applying the DVNN-LogTODIM-GRA technique to effectively manage MADM; (3) Conducting the numerical example to validate the effectiveness of the DVNN-LogTODIM-GRA for employment quality evaluation for university graduates.

2. Preliminaries

Kandasamy [38] constructed the DVNSs.

Definition 1 [38]. The DVNSs are constructed:

$$LA=\left\{\left(\theta,LT_A\left(\theta\right),LIT_A\left(\theta\right),LIF_A\left(\theta\right),LF_A\left(\theta\right)\right)\middle|\theta\in\Theta\right\}. \tag{1}$$

With truth-membership $LT_A\left(\theta\right)$, $LIT_A\left(\theta\right)$ stands for indeterminacy leaning towards $LT_A\left(\theta\right)$, $LIF_A\left(\theta\right)$ stands for indeterminacy leaning towards $LT_A\left(\theta\right)$ and falsitymembership $LF_A(\theta)$, $LT_A(\theta), LIT_A(\theta), LIF_A(\theta), LF_A(\theta) \in [0,1]$, $0 \le LT_A(\theta) + LIT_A(\theta) + LIF_A(\theta) + LF_A(\theta) \le 4$.

The DVNN is expressed as $LA = (LT_A, LIT_A, LIF_A, LF_A)$, where $LT_A, LIT_A, LIF_A, LF_A \in [0,1]$, $0 \le LT_A + LIT_A + LIF_A + LF_A \le 4$.

Definition 2[38]. Let $LA = (LT_A, LIT_A, LIF_A, LF_A)$ be DVNN, score value (SV) is conducted:

$$SV(LA) = \frac{(2 + LT_A + LIT_A - LIF_A - LF_A)}{4},\ SV(LA) \in [0,1]. \tag{2}$$

Definition 3[38]. Let $LA = (LT_A, LIT_A, LIF_A, LF_A)$ be DVNN, accuracy value (AV) is conducted:

$$AV(LA) = \frac{(LT_A + LIT_A + LIF_A + LF_A)}{4},\ AV(LA) \in [0,1]\ . \tag{3}$$

The order is constructed for DVNNs.

Definition 4[38]. Let $LA = (LT_A, LIT_A, LIF_A, LF_A)$ and $LB = (LT_B, LIT_B, LIF_B, LF_B)$, $SV(LA) = \frac{(2 + LT_A + LIT_A - LIF_A - LF_A)}{4}$, $SV(LB) = \frac{(2 + LT_B + LIT_B - LIF_B - LF_B)}{4}$, $AV(LA) = \frac{(LT_A + LIT_A + LIF_A + LF_A)}{4}$, $AV(LB) = \frac{(LT_B + LIT_B + LIF_B + LF_B)}{4}$, if $SV(LA) < SV(LB)$, $LA < LB$; if $SV(LA) = SV(LB)$, (1)if $AV(LA) = AV(LB)$, $LA = LB$; (2) if $AV(LA) < AV(LB)$, $LA < LB$.

Definition 5[38]. Let $LA = (LT_A, LIT_A, LIF_A, LF_A)$ and $LB = (LT_B, LIT_B, LIF_B, LF_B)$ be DVNNs, the operations are conducted:

(1) $LA \oplus LB = (LT_A + LT_B - LT_A LT_B, LIT_A + LIT_B - LIT_A LIT_B, LIF_A LIF_B, LF_A LF_B)$;

(2) $LA \otimes LB = (LT_A LT_B, LIT_A LIT_B, LIF_A + LIF_B - LIF_A LIF_B, LF_A + LF_B - LF_A LF_B)$;

(3) $\lambda LA = \left(1 - (1 - LT_A)^\lambda, 1 - (1 - LIT_A)^\lambda, (LIF_A)^\lambda, (LF_A)^\lambda\right), \lambda > 0$;

(4) $(LA)^\lambda = \left((LT_A)^\lambda, (LIT_A)^\lambda, 1 - (1 - LIF_A)^\lambda, 1 - (1 - LF_A)^\lambda\right), \lambda > 0$.

Definition 6[38]. Let $LA=\left(LT_A, LIT_A, LIF_A, LF_A\right)$ and $LB=\left(LT_B, LIT_B, LIF_B, LF_B\right)$, the DVNN Euclidean distance (DVNNED) between $LA=\left(LT_A, LIT_A, LIF_A, LF_A\right)$ and $LB=\left(LT_B, LIT_B, LIF_B, LF_B\right)$ is:

$$\begin{aligned} &DVNNED\left(LA, LB\right) \\ &=\sqrt{\frac{1}{4}\left(\left|LT_A-LT_B\right|^2+\left|LIT_A-LIT_B\right|^2+\left|LIF_A-LIF_B\right|^2+\left|LF_A-LF_B\right|^2\right)} \end{aligned} \quad (4)$$

3. Algorithm

3.1. MADM problem with DVNNs

The DVNN-LogTODIM-GRA technique is conducted for MADM. Let $LA=\left\{LA_1, LA_2, \cdots, LA_m\right\}$ be alternatives, and $LG=\left\{LG_1, LG_2, \cdots, LG_n\right\}$ be attributes with weight lw, where $lw_j \in \left[0,1\right]$, $\sum_{j=1}^{n} lw_j = 1$. Then, DVNN-LogTODIM-GRA technique is conducted for MADM (See Figure 1).

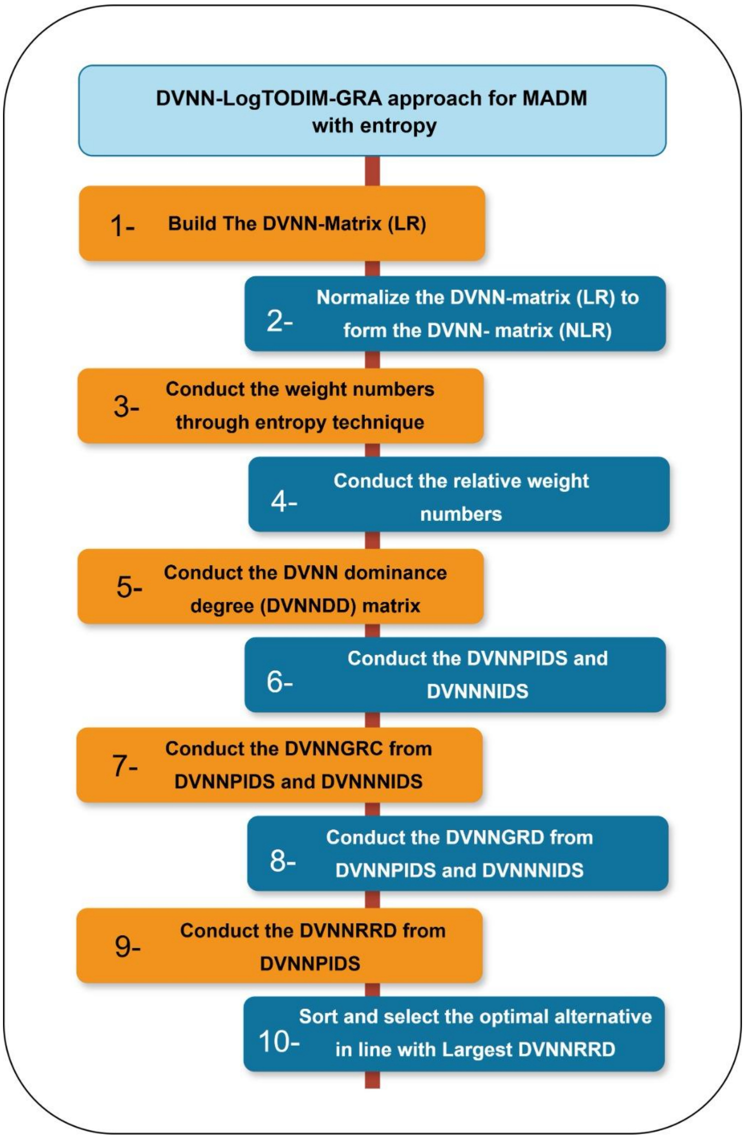

Figure 1. DVNN-LogTODIM-GRA approach for MADM with entropy

Step 1. Conduct the DVNN-matrix $LR = \left[LR_{ij}\right]_{m\times n} = \left(LT_{ij}, LIT_{ij}, LIF_{ij}\ LF_{ij}\right)_{m\times n}$

$$LR = \left[LR_{ij}\right]_{m\times n} = \begin{array}{c} \\ LA_1 \\ LA_2 \\ \vdots \\ LA_m \end{array} \begin{array}{c} \begin{array}{cccc} LG_1 & LG_2 & \dots & LG_n \end{array} \\ \begin{bmatrix} LR_{11} & LR_{12} & \dots & LR_{1n} \\ LR_{21} & LR_{22} & \dots & LR_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ LR_{m1} & LR_{m2} & \dots & LR_{mn} \end{bmatrix} \end{array} \tag{5}$$

Step 2. Normalize the $LR = \left[LR_{ij}\right]_{m\times n} = \left(LT_{ij}, LIT_{ij}, LIF_{ij}\ LF_{ij}\right)_{m\times n}$ into $NLR = \left[LR_{ij}\right]_{m\times n} = \left(NLT_{ij}, NLIT_{ij}, NLIF_{ij}\ NLF_{ij}\right)_{m\times n}$.

For benefit attributes:

$$NLR_{ij} = \left(LT_{ij}, LIT_{ij}, LIF_{ij}\ LF_{ij}\right) = \left(LT_{ij}, LIT_{ij}, LIF_{ij}\ LF_{ij}\right) \tag{6}$$

For cost attributes:

$$NLR_{ij} = \left(LT_{ij}, LIT_{ij}, LIF_{ij} LF_{ij} \right) = \left(LF_{ij}, LIF_{ij}, LIT_{ij} LT_{ij} \right) \tag{7}$$

3.2. Conduct the weight numbers through entropy.

Step 3. Conduct the weight numbers through entropy.

Entropy technique [39] is put forward obtaining weight numbers. The normalized DVNN-matrix $NDVNNM_{ij}$ is conducted:

$$NDVNNM_{ij} = \frac{\left(\begin{array}{l} SV\left(NLT_{ij}, NLIT_{ij}, NLIF_{ij} NLF_{ij} \right) \\ +AV\left(NLT_{ij}, NLIT_{ij}, NLIF_{ij} NLF_{ij} \right) \end{array} \right)}{\sum_{i=1}^{m} \left(\begin{array}{l} SV\left(NLT_{ij}, NLIT_{ij}, NLIF_{ij} NLF_{ij} \right) \\ +AV\left(NLT_{ij}, NLIT_{ij}, NLIF_{ij} NLF_{ij} \right) \end{array} \right)}, \tag{8}$$

The DVNN Shannon decision entropy (DVNNSDE) is managed:

$$DVNNSDE_{j} = -\frac{1}{\ln m} \sum_{i=1}^{m} NDVNNM_{ij} \ln NDVNNM_{ij} \tag{9}$$

and $NDVNNM_{ij} \ln NDVNNM_{ij} = 0$ if $NDVNNM_{ij} = 0$.

Then, the weight values $lw = \left(lw_1, lw_2, \cdots, lw_n \right)$ is conducted:

$$lw_{j} = \frac{1 - DVNNSDE_{j}}{\sum_{j=1}^{n} \left(1 - DVNNSDE_{j} \right)}, \quad j = 1, 2, 3, \cdots, n. \tag{10}$$

3.3. DVNN-LogTODIM-GRA approach for MADM

The DVNN-LogTODIM-GRA approach is conducted for MADM.

Step 4. Conduct relative weight:

$$rlw_{j} = lw_{j} \Big/ \max_{j} lw_{j}, \tag{11}$$

Step 5. Conduct the overall DVNN dominance degree (DVNNDD).

(1) The $DVNNDD_{j}\left(LA_{i}, LA_{\xi} \right)$ of LA_{i} over LA_{ξ} for LG_{j} is conducted:

$$DVNNDD_j\left(LA_i, LA_\xi\right) = \begin{cases} \dfrac{rlw_j \times \log\left(1+10\rho DVNNED\left(NLR_{ij}, NLR_{\xi j}\right)\right)}{\sum_{j=1}^{n} rlw_j} & \text{if } SV\left(NLR_{ij}\right) > SV\left(NLR_{\xi j}\right) \\ 0 & \text{if } SV\left(NLR_{ij}\right) = SV\left(NLR_{\xi j}\right) \\ -\dfrac{1}{\theta}\dfrac{\sum_{j=1}^{n} rlw_j \times \left(1-10^{-DVNNED\left(NLR_{ij}, NLR_{\xi j}\right)}\right)}{rlw_j} & \text{if } SV\left(NLR_{ij}\right) < SV\left(NLR_{\xi j}\right) \end{cases} \quad (12)$$

where $\lambda \in [1,5]$ and $\rho \in N^+$ is managed from agent's perception[36].

(2) The DVNNDD matrix $DVNNDD_j\left(LA_i\right)\left(j=1,2,\cdots,n\right)$ for LG_j is administrated:

$$DVNNDD_j\left(LA_i\right) = \left[DVNNDD_j\left(LA_i, LA_\xi\right)\right]_{m\times m}$$

$$= \begin{array}{c} \\ LA_1 \\ LA_2 \\ \vdots \\ LA_m \end{array} \begin{array}{c} \begin{array}{cccc} LA_1 & LA_2 & \cdots & LA_m \end{array} \\ \begin{bmatrix} 0 & DVNNDD_j\left(LA_1, LA_2\right) & \cdots & DVNNDD_j\left(LA_1, LA_m\right) \\ DVNNDD_j\left(LA_2, LA_1\right) & 0 & \cdots & DVNNDD_j\left(LA_2, LA_m\right) \\ \vdots & \vdots & \cdots & \vdots \\ DVNNDD_j\left(LA_m, LA_1\right) & DVNNDD_j\left(LA_m, LA_2\right) & \cdots & 0 \end{bmatrix} \end{array}$$

(3) Administrate the DVNNDD of LA_i for other alternatives under LG_j :

$$DVNNDD_j\left(LA_i\right) = \sum_{\xi=1}^{m} DVNNDD_j\left(LA_i, LA_\xi\right) \quad (13)$$

(4) The overall DVNNDD is conducted:

$$DVNNDD = \left(DVNNDD_{ij}\right)_{m\times n}$$

$$= \begin{bmatrix} & LG_1 & LG_2 & \ldots & LG_n \\ LA_1 & \sum_{\xi=1}^{m} DVNNDD_1\left(LA_1, LA_t\right) & \sum_{\xi=1}^{m} DVNNDD_2\left(LA_1, LA_t\right) & \ldots & \sum_{\xi=1}^{m} DVNNDD_n\left(LA_1, LA_t\right) \\ LA_2 & \sum_{\xi=1}^{m} DVNNDD_1\left(LA_2, LA_t\right) & \sum_{\xi=1}^{m} DVNNDD_2\left(LA_2, LA_t\right) & \ldots & \sum_{\xi=1}^{m} DVNNDD_n\left(LA_2, LA_t\right) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ LA_m & \sum_{\xi=1}^{m} DVNNDD_1\left(LA_m, LA_t\right) & \sum_{\xi=1}^{m} DVNNDD_2\left(LA_m, LA_t\right) & \ldots & \sum_{\xi=1}^{m} DVNNDD_n\left(LA_m, LA_t\right) \end{bmatrix}$$

Step 6. Conduct the DVNNPIDS (DVNN positive ideal decision solution) and DVNNNIDS (DVNN negative ideal decision solution):

$$DVNNPIDS = \left(DVNNPIDS_1, DVNNPIDS_1, \cdots, DVNNPIDS_n\right) \quad (14)$$

$$DVNNNIDS = \left(DVNNNIDS_1, DVNNNIDS_1, \cdots, DVNNNIDS_n\right) \tag{15}$$

$$DVNNPIDS_j = \max_{j=1}^{n} DVNNDD_{ij}, DVNNNIDS_j = \min_{j=1}^{n} DVNNDD_{ij} \tag{16}$$

Step 7. Conduct the DVNNGRC (DVNN grey rational coefficients) from DVNNPIDS and DVNNNIDS:

$$DVNNGRC\left(LA_{ij}, DVNNPIDS_j\right) = \frac{\min\limits_{1\le i\le m}\min\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right| + \rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|}{\left|DVNNDD_{ij} - DVNNPIDS_j\right| + \rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|} \tag{17}$$

$$DVNNGRC\left(LA_{ij}, DVNNNIDS_j\right) = \frac{\min\limits_{1\le i\le m}\min\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right| + \rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right|}{\left|DVNNDD_{ij} - DVNNNIDS_j\right| + \rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right|} \tag{18}$$

Step 8. Conduct the DVNNGRD (DVNN grey relation degree) from DVNNPIDS and DVNNNIDS:

$$\begin{aligned} &DVNNGRD\left(LA_i, DVNNPIDS\right) \\ &= \sum_{j=1}^{n}\left(lw_j \times DVNNGRC\left(LA_{ij}, DVNNPIDS_j\right)\right) \\ &= \sum_{j=1}^{n}\left(lw_j \times \frac{\left(\begin{array}{l}\min\limits_{1\le i\le m}\min\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right| \\ +\rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|\end{array}\right)}{\left(\begin{array}{l}\left|DVNNDD_{ij} - DVNNPIDS_j\right| \\ +\rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|\end{array}\right)}\right) \end{aligned} \tag{19}$$

$$\begin{aligned} &DVNNGRD\left(LA_i, DVNNNIDS\right) \\ &= \sum_{j=1}^{n}\left(lw_j \times DVNNGRC\left(LA_{ij}, DVNNNIDS_j\right)\right) \\ &= \sum_{j=1}^{n}\left(lw_j \times \frac{\left(\begin{array}{l}\min\limits_{1\le i\le m}\min\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right| \\ +\rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right|\end{array}\right)}{\left(\begin{array}{l}\left|DVNNDD_{ij} - DVNNNIDS_j\right| \\ +\rho\max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right|\end{array}\right)}\right) \end{aligned} \tag{20}$$

Step 9. Conduct the DVNNRRD (DVNN relative relational degree) from DVNNPIDS.

$$DVNNRRD\left(LA_i, DVNNPIDS\right) = \frac{DVNNGRD\left(LA_i, DVNNPIDS\right)}{DVNNGRD\left(LA_i, DVNNNIDS\right) + DVNNGRD\left(LA_i, DVNNPIDS\right)}$$

$$= \frac{\sum_{j=1}^{n}\left(lw_j \times \frac{\left(\begin{array}{l}\min\limits_{1\le i\le m}\min\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right| \\ +\rho \max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|\end{array}\right)}{\left(\begin{array}{l}\left|DVNNDD_{ij} - DVNNPIDS_j\right| \\ +\rho \max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|\end{array}\right)}\right)}{\left(\begin{array}{l}\sum_{j=1}^{n}\left(lw_j \times \frac{\left(\begin{array}{l}\min\limits_{1\le i\le m}\min\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right| \\ +\rho \max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right|\end{array}\right)}{\left(\begin{array}{l}\left|DVNNDD_{ij} - DVNNNIDS_j\right| \\ +\rho \max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNNIDS_j\right|\end{array}\right)}\right) \\ +\sum_{j=1}^{n}\left(lw_j \times \frac{\left(\begin{array}{l}\min\limits_{1\le i\le m}\min\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right| \\ +\rho \max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|\end{array}\right)}{\left(\begin{array}{l}\left|DVNNDD_{ij} - DVNNPIDS_j\right| \\ +\rho \max\limits_{1\le i\le m}\max\limits_{1\le j\le n}\left|DVNNDD_{ij} - DVNNPIDS_j\right|\end{array}\right)}\right)\end{array}\right)} \tag{21}$$

Step 10. Sort and select the optimal alternative with the largest DVNNRRD.

4. Analysis and Discussion

The evaluation of university employment quality is a key process in systematically assessing the performance of graduates in the job market. Its purpose is to analyze data from multiple dimensions to measure the alignment between university talent cultivation and market demands, thereby providing a basis for improving teaching and management in universities. Employment quality evaluation not only focuses on the employment rate of graduates but also includes various aspects of employment quality, such as the relevance of job positions to their major, salary levels, job stability, career development prospects, and satisfaction from both graduates and employers. Firstly, the employment rate is one of the most basic metrics, reflecting the percentage of graduates who find jobs within a certain period. However, relying solely on the employment rate does not comprehensively reflect employment quality. Therefore, the evaluation also needs to examine the match between job positions and majors, as well as the application of graduates' skills in their jobs. A high degree of job-major alignment indicates that the university is effectively responding to industry demands, highlighting the effectiveness of curriculum design, teaching content, and practical skill development. Secondly, salary levels are another important indicator, often used as an indirect measure of graduates' competitiveness in the job market. The salary level not only reflects the demand for specific industries but also, to some extent, indicates the professional skills and market recognition of the graduates. Additionally, the potential for salary growth can help assess the long-term career development opportunities of graduates. Job stability and career development prospects are also crucial aspects of employment quality evaluation. Job stability refers to the continuity of employment over a certain period, which reflects graduates' adaptability to their positions and job-market fit. Career development prospects focus on the long-term growth opportunities and career advancement of graduates, helping to assess their job satisfaction and career planning. Lastly, feedback from both graduates and employers is an important source of information for employment quality evaluation. Surveys on graduates' job satisfaction can help understand their level of contentment with their current employment and their feedback on university education. Employer feedback provides insights into the professional qualities, work attitudes, and skills of graduates, enabling universities to adjust their talent cultivation strategies accordingly. In summary, the evaluation of university employment quality is a multidimensional, comprehensive assessment process. Through data analysis and feedback collection, it aims to help universities improve educational quality and enhance the alignment between talent cultivation and market demand. The employment quality evaluation for university graduates is MADM. There are seven potential local applied undergraduate colleges $LA_i\left(i=1,2,3,4,5,6,7\right)$ are evaluated from four attributes: ①LLG_1 is Employment Rate-The employment rate is the most basic evaluation indicator, reflecting the proportion of graduates who find jobs within a certain period. It is commonly used to measure the overall performance of students trained by universities in the job market and serves as one of the fundamental indicators for assessing employment quality; ②LLG_2 is the Job-Major Relevance- This indicator measures the degree of alignment between the job held by a graduate and their field of study. High relevance indicates that the university’s curriculum and program design align well with market demands, and the skills taught are consistent with industry requirements; ③LLG_3 is the Salary Level- Salary level is an important economic indicator of employment quality, reflecting the market competitiveness of graduates and the value of the positions they hold. A higher salary typically signals better career development opportunities and higher job requirements; ④LLG_4 is Job Stability-Job stability refers to a graduate’s ability to maintain long-term employment after securing a job. It reflects graduates' adaptability to their positions, the degree of job fit, and their recognition by employers. It is a long-term dimension used to assess employment quality. The seven potential local applied undergraduate colleges $LA_i\left(i=1,2,3,4,5,6,7\right)$ are evaluated under DVNNs through four attributes.

The DVNN-LogTODIM-GRA technique is put forward the employment quality evaluation for university graduates.

Step 1. Administrate the DVNN-matrix $LR=\left[LR_{ij}\right]_{7\times4}=\left(LT_{ij},LIT_{ij},LIF_{ij}\,LF_{ij}\right)_{7\times4}$ (See Table 1).

Table 1. DVNN information

	LLG2	LLG2
LA1	(0.23, 0.29,0.61, 0.45)	(0.23, 0.46, 0.96, 0.38)
LA2	(0.34, 0.65, 0.26, 0.82)	(0.37, 0.82, 0.43, 0.69)
LA3	(0.58, 0.35, 0.19, 0.43)	(0.32, 0.94, 0.62, 0.76)
LA4	(0.53, 0.89, 0.46, 0.23)	(0.16, 0.37, 0.29, 0.15)
LA5	(0.38, 0.69, 0.74, 0.16)	(0.27, 0.58, 0.37, 0.41)
LA6	(0.39, 0.56, 0.17, 0.65)	(0.62, 0.29, 0.75, 0.52)
LA7	(0.83, 0.17, 0.33, 0.27)	(0.29, 0.53, 0.69, 0.86)
	LLG3	LLG4
LA1	(0.49, 0.45, 0.17, 0.43)	(0.22, 0.48, 0.37, 0.68)
LA2	(0.23, 0.67, 0.47, 0.83)	(0.46, 0.51, 0.65, 0.72)
LA3	(0.47, 0.83, 0.41, 0.17)	(0.31, 0.54, 0.64, 0.46)
LA4	(0.26, 0.56, 0.26, 0.78)	(0.45, 0.79, 0.46, 0.69)
LA5	(0.27, 0.49, 0.73, 0.39)	(0.31, 0.59, 0.28, 0.64)
LA6	(0.31, 0.63, 0.67, 0.12)	(0.51, 0.17, 0.64, 0.41)
LA7	(0.78, 0.12, 0.28, 0.21)	(0.32, 0.63, 0.32, 0.29)

Step 2. Normalize the $LR=\left[LR_{ij}\right]_{7\times4}$ into $NLR=\left[NLR_{ij}\right]_{7\times4}$ (See Table 2).

Table 2. The $NLR=\left[NLR_{ij}\right]_{7\times4}$

	LLG2	LLG2
LA1	(0.23, 0.29,0.61, 0.45)	(0.23, 0.46, 0.96, 0.38)
LA2	(0.34, 0.65, 0.26, 0.82)	(0.37, 0.82, 0.43, 0.69)
LA3	(0.58, 0.35, 0.19, 0.43)	(0.32, 0.94, 0.62, 0.76)
LA4	(0.53, 0.89, 0.46, 0.23)	(0.16, 0.37, 0.29, 0.15)

LA_5	(0.38, 0.69, 0.74, 0.16)	(0.27, 0.58, 0.37, 0.41)
LA_6	(0.39, 0.56, 0.17, 0.65)	(0.62, 0.29, 0.75, 0.52)
LA_7	(0.83, 0.17, 0.33, 0.27)	(0.29, 0.53, 0.69, 0.86)
	LLG_3	LLG_4
LA_1	(0.49, 0.45, 0.17, 0.43)	(0.22, 0.48, 0.37, 0.68)
LA_2	(0.23, 0.67, 0.47, 0.83)	(0.46, 0.51, 0.65, 0.72)
LA_3	(0.47, 0.83, 0.41, 0.17)	(0.31, 0.54, 0.64, 0.46)
LA_4	(0.26, 0.56, 0.26, 0.78)	(0.45, 0.79, 0.46, 0.69)
LA_5	(0.27, 0.49, 0.73, 0.39)	(0.31, 0.59, 0.28, 0.64)
LA_6	(0.31, 0.63, 0.67, 0.12)	(0.51, 0.17, 0.64, 0.41)
LA_7	(0.78, 0.12, 0.28, 0.21)	(0.32, 0.63, 0.32, 0.29)

Step 3. Conduct the weight: $lw_1 = 0.2654, lw_2 = 0.3475, lw_3 = 0.2057, lw_4 = 0.1814$.

Step 4. Conduct the relative weight: $rlw = \{0.7637, 1.0000, 0.5919, 0.5220\}$

Step 5. Conduct the $DVNNDD = \left(DVNNDD_{ij}\right)_{5\times4}$ (Table 3):

Table 3. The $DVNNDD = \left(DVNNDD_{ij}\right)_{5\times4}$

	LLG_1	LLG_2	LLG_3	LLG_4
LA_1	-0.4911	0.8640	-1.2548	-0.9078
LA_2	-1.1168	-1.6364	0.8443	-0.5024
LA_3	-0.2610	0.9378	0.8724	-1.4700
LA_4	0.2862	0.2018	-0.6111	-0.0469
LA_5	-1.8989	0.4759	0.3379	-0.5879
LA_6	-0.2663	1.1191	-1.9159	0.4796
LA_7	0.2810	0.3831	0.3549	-0.5916

Step 6. Administrate the DVNNPIDS and DVNNNIDS (Table 4).

Table 4. DVNNPIDS and DVNNNIDS

	LLG_1	LLG_2	LLG_3	LLG_4
DVNNPIDS	0.2862	1.1191	0.8724	0.4796
DVNNNIDS	-1.8989	-1.6364	-1.9159	-1.4700

Step 7. Calculate the $DVNNGRC\left(LA_{ij}, DVNNPIDS_j\right)$ and $DVNNGRC\left(LA_{ij}, DVNNNIDS_j\right)$ (See table 5-6).

Table 5. The $DVNNGRC\left(LA_{ij}, DVNNPIDS_j\right)$

	LLG$_1$	**LLG$_2$**	**LLG$_3$**	**LLG$_4$**
LA$_1$	0.6420	0.8453	0.3959	0.5012
LA$_2$	0.4984	0.3360	0.9802	0.5867
LA$_3$	0.7181	0.8849	1.0000	0.4169
LA$_4$	1.0000	0.6031	0.4845	0.7259
LA$_5$	0.3895	0.6843	0.7229	0.5664
LA$_6$	0.7162	1.0000	0.3333	1.0000
LA$_7$	0.9962	0.6545	0.7293	0.5655

Table 6. The $DVNNGRC\left(LA_{ij}, DVNNNIDS_j\right)$

	LLG$_1$	**LLG$_2$**	**LLG$_3$**	**LLG$_4$**
LA$_1$	0.4976	0.3580	0.6783	0.7126
LA$_2$	0.6406	1.0000	0.3356	0.5903
LA$_3$	0.4598	0.3513	0.3333	1.0000
LA$_4$	0.3895	0.4313	0.5166	0.4949
LA$_5$	1.0000	0.3976	0.3822	0.6125
LA$_6$	0.4606	0.3360	1.0000	0.4169
LA$_7$	0.3901	0.4084	0.3804	0.6135

Step 8. Calculate the $DVNNGRD\left(LA_i, DVNNPIDS\right)$ and $DVNNGRD\left(LA_i, DVNNNIDS\right)$ (See table 7-8).

Table 7. The $DVNNGRD\left(LA_i, DVNNPIDS\right)$ and $DVNNGRD\left(LA_i, DVNNNIDS\right)$

Alternative	$DVNNGRD\left(LA_i, DVNNPIDS\right)$	$DVNNGRD\left(LA_i, DVNNNIDS\right)$

LA_1	0.6365	0.5253
LA_2	0.5571	0.6936
LA_3	0.7794	0.4941
LA_4	0.7063	0.4493
LA_5	0.5926	0.5933
LA_6	0.7875	0.5203
LA_7	0.7444	0.4350

Step 9. Administrate the $DVNNRRD\left(LA_i, DVNNPIDS\right)$ from DVNNPIDS (See table 9).

Table 9. The $DVNNRRD\left(LA_i, DVNNPIDS\right)$ and order

Alternative	$DVNNRRD\left(LA_i, DVNNPIDS\right)$	**Order**
LA_1	0.5479	5
LA_2	0.4454	7
LA_3	0.6120	2
LA_4	0.6112	3
LA_5	0.4997	6
LA_6	0.6022	4
LA_7	0.6312	1

Step 9. From the $DVNNRRD\left(LA_i, DVNNPIDS\right)$, the order is: $LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$. Thus, the optimal local applied undergraduate college is LA_7.

5. Comparative analysis

Then, the DVNN-LogTODIM-GRA technique is compared with generalized double-valued neutrosophic weighted distance [38] and weighted Dice similarity measures $WD_{\mathrm{DVNS}_1}\left(HA_i, DVNNPIS\right)$, $WD_{\mathrm{DVNS}_2}\left(HA_i, DVNNPIS\right)$ and weighted generalized Dice similarity measures $WGD_{\mathrm{DVNS}_1}\left(HA_i, DVNNPIS\right), WGD_{\mathrm{DVNS}_2}\left(HA_i, DVNNPIS\right)$[40], DVNN-

Taxonomy technique [41], DVNN-CoCoSo technique [42] and DVNN-TODIM-VIKOR technique [43]. The final comparative results are shown in Table 10.

Table 10. Order of different techniques

Different Techniques	**Order**
DVNN weighted Hamming distance[38]	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$
DVNN weighted Euclidean distance[38]	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$
$WD_{\mathrm{DVNS}_1}\left(HA_i, DVNNPIS\right)$ *[40]*	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$
$WD_{\mathrm{DVNS}_2}\left(HA_i, DVNNPIS\right)$ *[40]*	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$
$WGD_{\mathrm{DVNS}_1}\left(HA_i, DVNNPIS\right)$ *[40]*	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$
$WGD_{\mathrm{DVNS}_2}\left(HA_i, DVNNPIS\right)$ *[40]*	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$
DVNN-Taxonomy method[41]	$LA_7 > LA_3 > LA_4 > LA_6 > LA_5 > LA_1 > LA_2$
DVNN-CoCoSo technique [42]	$LA_7 > LA_3 > LA_4 > LA_6 > LA_5 > LA_1 > LA_2$
DVNN-TODIM-VIKOR technique [43]	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$
DVNN-LogTODIM-GRA technique	$LA_7 > LA_3 > LA_4 > LA_6 > LA_1 > LA_5 > LA_2$

Based on the above analysis, it can be concluded that while the ranking of these techniques may differ slightly, they all consistently identify the same optimal and worst local applied vocational undergraduate colleges. This consistency supports the validity of the DVNN-LogTODIM-GRA technique. The key strengths of DVNN-LogTODIM-GRA are as follows: (1) It accounts for the psychological behavior of decision-makers and the shape similarity between DVNNPIDS and DVNNNIDS when evaluating employment quality. (2) It integrates the complex behavior of the LogTODIM and GRA techniques, making it a robust MAGDM tool for assessing employment quality. However, its main drawback is its inability to address consensus issues during the evaluation of university graduate employment quality.

6. Conclusion

The evaluation of university employment quality is a key system of indicators that measures the performance of graduates in the job market. It not only focuses on the employment rate of graduates but also assesses multiple dimensions of employment quality, including the relevance of jobs to their field of study, salary levels, job stability, and career development prospects. Through these indicators, universities can understand how well their talent cultivation aligns with market demands and optimize their curriculum and teaching methods. Additionally, employment quality evaluation incorporates feedback from both graduates and employers, analyzing graduates' professional skills, job performance, and employer satisfaction. This evaluation system helps universities continuously improve education quality, enhance graduates' competitiveness in the job market, and provide important decision-making insights for future educational improvements. The employment quality evaluation for university graduates involves MADM. Currently, the LogTODIM and GRA techniques are widely applied to address multi-attribute decision-making (MADM) challenges. To manage uncertain information in this evaluation, DVNSs (Dual-Valued Neutrosophic Sets) are used as a characterization tool. This study introduces the DVNN-LogTODIM-GRA technique to solve MADM problems under DVNSs. To validate the proposed method, a numerical example is provided, focusing on the evaluation of employment quality for university graduates. The key contributions of this study are as follows: (1) The use of the entropy method to determine weight values under DVNSs; (2) The application of DVNN-LogTODIM-GRA to effectively handle MADM problems; (3) The validation of the DVNN-LogTODIM-GRA technique through a numerical example related to university graduate employment quality evaluation.

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