Iranian Journal of Operations Research
Vol. 17, No. 1, 2026, pp. 1-19

A New Decision- Making Method Based on Shannon Entropy

H. Babaei Meybodi[1]*, SH. Mohammadi Ardakani[2], H. Ghaneai[3]

In multi-criteria decision-making (MCDM), assigning proper weights to criteria is a critical step because criteria do not contribute equally to the final choice. This study introduces a new dispersion-based weighting method (DWM), which determines criterion weights using the mean, standard deviation, and coefficient of variation of the decision matrix. The method is formulated in five steps and tested through several numerical examples. Its performance is evaluated by comparison with Shannon entropy. The results reveal a very strong correlation between the two methods, with Pearson correlation coefficients of 0.997 and 0.979 in the two cases considered. Moreover, in Example 3.1, all criterion values and rankings were identical in both methods, whereas in Example 3.2, only criterion 5 exhibited a discrepancy. Overall, the proposed method offers low computational complexity, eliminates the need for normalization, and can be applied to negative data, making it a practical alternative for objective weighting in MCDM.

Keywords: *Multiple Criteria Decision Making (MCDM), Multi-Objective Decision Making (MODM), Multi-Attribute Decision Making (MADM), Shannon Entropy.*

1. Introduction

Choosing the optimal alternative has always been a challenging task. When decision-making becomes difficult due to the presence of multiple options and the need to evaluate numerous indicators, the application of Multiple Criteria Decision-Making (MCDM) methods is recommended [2,11], as this field constitutes a highly important part of decision-making theory [42]. In multi-criteria decision-making approaches, several criteria are considered instead of relying on a single measure of optimality, and these methods have been extensively examined by scholars over recent decades. The stages of problem-solving and decision-making shape the overall direction through which an organization pursues its objectives. Management plays a vital role in this process, as the quality of plans and programs, the effectiveness and efficiency of strategies, and the outcomes derived from their implementation all depend heavily on the quality of managerial decisions. In essence, management quality is fundamentally a function of decision-making quality. Moreover, when decisions are based on multiple criteria, the resulting choice is generally more desirable and satisfactory for the decision-maker [32]. The presence of multiple stakeholders with differing interests and values further complicates the decision-making process [24].

On the other hand, indicators do not have the same level of importance in decision-making processes. In such cases, it is necessary to determine the significance of these indicators and assign an appropriate weight to each of them. The weight of each indicator reflects its relative importance

*Corresponding author: Tel: +98(912)8490630, E-mail: babaei@meybod.ac.ir.
[1]Department of Management, Meybod University, Meybod, Iran.
[2]Department of Management, Yazd University, Yazd, Iran.
[3]Department of Computer Engineering, Meybod University, Meybod, Iran.

compared with other indicators [34]. Careful and accurate determination of these weights plays a crucial role in achieving reliable results. Although a considerable number of multi-criteria decision-making (MCDM) methods were developed in the previous century, for example [21], their widespread application and certain limitations have motivated researchers to develop new methods or improve existing ones, as discussed in [20,42,13].

There are two main categories of multi-criteria decision-making (MCDM) methods: Multi-Objective Decision Making (MODM) and Multi-Attribute Decision Making (MADM) [31]. The overall purpose of decision-making is either to identify the most suitable alternative or to balance multiple decision variables. Each class of decision-making techniques serves a distinct function some determine the weights of criteria, others rank the available alternatives, and some evaluate the criteria themselves. MODM approaches are generally applied in design-oriented problems, whereas MADM methods are primarily used to select the most preferable alternative, which is the central focus of this study. The essential distinction between MODM and MADM models is that the former operates within a continuous decision space, while the latter is defined in a discrete decision space [27].

The importance of indicators in decision-making is clearly not the same, and therefore their relative significance must be determined. In such situations, it is necessary to calculate the relevance coefficient or weight of each indicator, which reflects its importance compared to other indicators [22,44]. The careful and accurate assignment of weights plays a critical role in achieving reliable and meaningful results. Several well-established methods exist for determining criteria weights. Among the most widely used are the Analytic Hierarchy Process (AHP) [39,30,5], the Analytic Network Process (ANP) [47,28,41], the Entropy Weighting Method (EWM) [5,49], the CRITIC method (Criteria Importance Through Intercriteria Correlation) [1,15], and the Bulls-eye method [4]. In addition, more recent approaches such as the Superiority and Inferiority Ranking (SIR) method [48], the Stepwise Weight Assessment Ratio Analysis (SWARA) method [45], the Best–Worst Method (BWM) [37,38], and the Importance Weight Estimation (IMP) method [16] have been increasingly employed in contemporary decision-making applications. Although many multi-criteria decision-making (MCDM) methods have been developed over time, their widespread application and certain inherent limitations have motivated researchers to introduce new approaches and improved versions of existing techniques. These developments aim to enhance the accuracy, reliability, and effectiveness of decision-making processes in complex environments, as highlighted in several recent studies [14,35,7,36].

One of the most widely used approaches for ranking alternatives and assessing the relative importance of criteria through pairwise comparisons is the hierarchical analysis method [8]. This approach is also applied to determine criteria weights. As the number of elements within each group increases, paired comparisons become more complex; therefore, decision criteria are often divided into sub-criteria. The CRITIC method [1], offers another way to derive criteria weights. This approach places less emphasis on expert judgment, which is one of its key advantages. Instead, the method evaluates data based on the degree of contrast and conflict among the criteria [29]. The Best–Worst Method (BWM) is considered one of the more recent techniques in multi-criteria decision-making [3,37]. In this method, the decision-maker identifies the best and worst criteria, and pairwise comparisons are then made between these two and the remaining criteria. An optimization model is subsequently formulated and solved to estimate the weights. Moreover, the method includes a measure to check the consistency of the comparisons [10].

One of the multi-criteria decision-making approaches used to determine criteria weights in a three-parameter gray number spectrum is the Bull's-eye method [46]. In decision matrices, this method utilizes three parameters for weighting. By reducing reliance on expert judgments and recalculating the weights, the Bull's-eye approach can significantly decrease the influence of subjective human judgments in the criteria weighting process [17]. Another widely used multi-criteria decision-making method is the SWARA technique (Step-wise Weight Assessment Ratio Analysis), which is applied to determine the weights of criteria and sub-criteria [25]. In this approach, criteria are first arranged according to their relative importance. The most important criterion is placed at the top of the list, while the least important criterion appears at the end. Experts (respondents) play a crucial role in determining the weights of the criteria in this method. A key feature of the SWARA technique is its ability to incorporate expert evaluations regarding the importance of criteria during the weighting process [12]. This method can therefore be used to collect and organize information obtained from experts and specialists [43]. In information theory, entropy is used to measure the amount of information contained in a message [20]. Because the decision matrix of a set of alternatives includes a certain level of information, entropy can be used to evaluate the characteristics of the criteria [23]. The entropy method is a dispersion-based multi-criteria decision-making technique that determines criteria weights according to the degree of variation among them [23,33]. The fundamental assumption of this method is that the greater the dispersion in the values of a criterion, the more important that criterion is considered to be [40]. Conversely, if all alternatives have identical values for a particular criterion, that criterion can be removed from the analysis [18].

2. Research gap

Although many multi-criteria decision-making methods have been developed over time, their widespread application and certain limitations have motivated researchers to introduce new approaches and improved versions of existing techniques to enhance the accuracy, reliability, and effectiveness of decision-making processes in complex environments. However, there is still a need for objective weighting methods that are simpler, avoid complex mathematical transformations, and can be applied directly to raw data without requiring normalization or imposing restrictions on the presence of negative values. Accordingly, this study aims to address this gap by proposing a dispersion-based weighting method (DWM) that determines criteria weights using basic statistical dispersion measures, providing a more straightforward, flexible, and computationally efficient alternative to existing methods.

3. Proposed Method

The following matrix representation can be used to fully characterize a multi-attribute decision-making problem:

$$B = \begin{matrix} \\ a_1 \\ a_2 \\ \vdots \\ a_m \end{matrix} \begin{matrix} c_1 & c_2 & \cdots & c_n \\ \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mn} \end{pmatrix} \end{matrix}$$

The ith option is represented by a_i, the jth criteria is represented by C_j and the value of the ith option in terms of the jth criteria is represented by p_{ij}. The objective is to pick the best choice (the one that is most desirable and important), or an alternative that has the best overall value. Various approaches may be used to determine the alternative value of alternative v_i. In general, if we give the weight w_j to the criteria j ($w_j \geq 0, \sum w_j = 1$)، we may get v_i using the simple weighting technique [31], which is the foundation for many MCDM systems, as follows:

The approach for obtaining standard or vector weights $w = \{w_1, w_2, \ldots, w_n\}$ is highly essential here, and it is the rationale for creating various MCDM systems in recent decades.

A careful and accurate selection of weights plays a crucial role in achieving the desired outcome. Once the data for the decision matrix have been properly prepared, the entropy method can be applied to determine the weights of the indicators. Entropy is a key concept in the social sciences, physics, and information theory, and this method requires a criterion–alternative matrix. The approach was introduced by Shannon and Weaver in 1974. Entropy represents the degree of uncertainty in a continuous probability distribution. The fundamental idea is that the greater the variability in the values of an index, the more important that index becomes. Shannon showed that events with a high probability of occurrence convey less information, while events with a low probability convey more. When new information is obtained, uncertainty is reduced, and the value of this information corresponds to the amount of uncertainty eliminated. Therefore, uncertainty and information are inherently linked. However, in many cases, the weights produced by the entropy method may seem unreasonable, and the method itself involves multiple steps and extensive calculations.

The purpose of this study is to introduce a new weighting technique (WBI) that is computationally more efficient than traditional entropy-based methods. We demonstrate that one of the key advantages of the proposed approach is its significantly lower computational burden compared to the Shannon entropy method, as well as the fact that it does not require data normalization. As a result, this method can assist researchers in addressing decision-making problems involving a large number of variables. The remainder of this article is organized as follows. Section 2 introduces the new technique (DWM). Section 3 applies DWM to a real-world case and compares its entropy performance using various evaluation criteria. Section 4 presents conclusions and suggestions for future research.

3.1. Dispersion-based Weighting Method (DWM)

The weighting of components plays a vital role in most multi-criteria decision-making processes. Entropy, a concept widely used in the social sciences, physics, and information theory, is also employed as a method for determining the weights of criteria in MCDM. This approach requires constructing a matrix consisting of criteria and alternatives. When the data for the decision matrix are available, the entropy method can be applied to calculate the corresponding weights. According to the Shannon entropy principle, criteria with greater variability in their values are assigned higher weights, indicating their stronger influence on selecting the optimal alternative [9].

3.1.1. Shannon entropy method

Step 1: The decision matrix is created first. To create this matrix, just determine whether the criteria are qualitative, assess each choice in respect to each criterion using verbal phrases, and, if the criteria are small, enter the real number of that evaluation. The criteria are listed in the columns, and the alternatives are shown in the rows in the decision matrix shown below. The score of the first choice, for example, is x_{12} when compared to the second criterion.

$$X_{ij} = [x_{ij}]_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \qquad (1)$$

Step 2: Each normalized flow is called after the aforementioned matrix is normalized. Normalization is done linearly in the Shannon entropy approach. In this method, each column's knowledge is split by the total of that column's knowledge.

$$[P_{ij}]_{n\times m} = \left[\frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}\right]_{n\times m} \qquad (2)$$

Step 3: Calculating the entropy of each index: Shannon used the following formula to calculate the entropy of a probability distribution for each random phenomenon:

$$E = S\begin{pmatrix} P_1 \\ P_2 \\ \vdots \\ P_m \end{pmatrix}, \sum_{i=1}^{m} P_i = 1$$

The following formula was proposed to compute the entropy of such events, which, due to the uncertainty of the numbers within the matrix, also contain the indice0s:

$$E_j = -k \sum_{i=1}^{m} [P_i . \ln P_i] , k = \frac{1}{\ln(m)} \qquad (3)$$

Where Ej is the index's entropy is j, the number of choices is m. From the perspective of the i, Pi option, the likely value of the index value, ln is the symbol for the neper logarithm or natural logarithm, and k is a constant number for modifying entropy between 0 and 1.

It's worth noting that in decision matrices, it's usually m ≥3, which means that if there are fewer than three alternatives, it's not as essential, so:

$$\frac{1}{\ln(m)}, (m = 3 > e = 2.7 \rightarrow \ln(m) > 1 \rightarrow \frac{1}{\ln(m)} < 1)$$

In this formula, the closer Ej, the jth index's entropy, goes to one, the less the index's influence on prioritizing alternatives is decreased to zero. As a result, if a phenomena or index has the same probability as all other alternatives, its entropy will be one hundred percent and one, and it will therefore have no part in the choosing of the option, which appears apparent. This is also described mathematically in broad terms as follows. It will if an index has the same value from the point of view of the m option. Therefore:

$$E_j = -k \sum_{i=1}^{m} [P_i . \ln(P_i)] = -\frac{1}{\ln(m)} [P_1 \ln(P_1), P_2 \ln(P_2), \ldots, P_m \ln(P_m)]$$
$$= -\frac{1}{\ln(m)} \left[\frac{1}{m} \ln\frac{1}{m}, \frac{1}{m} \ln\frac{1}{m}, \ldots, \frac{1}{m} \ln\frac{1}{m}\right] = -\frac{1}{\ln(m)} \left[m(\frac{1}{m} \ln\frac{1}{m})\right]$$

$$= -\frac{1}{ln(m)}\left[1 \times ln\frac{1}{m}\right] = -\frac{1}{ln(m)}[-ln(m)] \Rightarrow E_j = 1$$

That is, such an index is completely entropic, plays no part in option selection, and has no weight, as will be shown.

Step 4: The dj value (degree of deviation) is then calculated, which indicates how much usable information the relevant index (dj) offers to the decision-maker. The more dissimilar the competing choices are in terms of that index, the closer the measured values of the index are to each other.

$$d_j = 1 - E_j, j = 1,2,\ldots,n \tag{4}$$

Step 5: The following equation is used to calculate the weight of each index:

$$W_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, j = 1,2,\ldots,n \tag{5}$$

One of the suitable ways for weighing the criteria is the method presented in this study (WBI). This technique is data-driven, similar to the Shannon entropy method, in that the weight of the criterion is determined by the relationship between the decision matrix data. This approach uses the same reasoning as the entropy method of data dispersion, thus the criteria with the most dispersed data will be more significant for decision making. As a result, he is likely to gain weight.

Low computing burden and simplicity are two advantages of the suggested technique over the Shannon entropy method. Because the data does not need to be normalized. Another benefit of this approach over entropy is that it can be used to calculate negative data, whereas Ln in the Shannon entropy method cannot calculate. Indifference indicates that criteria with zero dispersion has no influence on the decision-maker's choice. DWM stands for Dispersion-based Weighting Method.

3.1.2. Dispersion-based Weighting Method

Step 1: The decision matrix is constructed in the same way as Shannon's entropy technique:

$$X_{ij} = [x_{ij}]_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{6}$$

Step 2: Calculate each criterion's average μ_j, which is determined as follows:

$$\mu_j = \frac{\sum_{i=1}^{n} x_{ij}}{n}, i = 1,2,\ldots,n, j = 1,2,\ldots,m$$

Where n is the number of options and m is the number of criteria.

Step 3: Calculate each criterion's standard deviation s_j which is determined as follows:

$$s_j = \sqrt{\frac{(\sum_{i=1}^{n} x_{ij} - \mu_j)^2}{n}}, i = 1,2,\ldots,n, j = 1,2,\ldots,m$$

Step 4: Calculate each criterion's coefficient of variation vc_j as follows:

$$vc_j = \frac{s_j}{\mu_j}, j = 1,2, \dots, m$$

Step 5: Use the following equation to calculate the weight of each criterion w_j:

$$w_j = \frac{vc_j}{\sum_{j=1}^{m} vc_j}, j = 1,2, \dots, m$$

4. Numerical examples

In this part, we look at two distinct instances to demonstrate the validity of the suggested technique and to show how it differs from the Shannon entropy method.

Example 4. 1

Assume a recent university graduate wishes to select one of four occupations based on five indications. Income, social position, hard labor, distance, and social security are all indicators. Table 1 shows the worth of each position in terms of each metric.

Table1. Decision Matrix

Cj / Ai	Income	Social image	Hard work	Distance	Security
	C1	**C2**	**C3**	**C4**	**C5**
A1	15	High	Relatively high	10	High
A2	12	Medium	Medium	3	Extremely high
A3	20	Extremely high	High	30	Medium
A4	30	Low	Extremely high	1	Low

Two of the five accessible indications (C1, C4) are quantitative, while the others are qualitative, according to this choice matrix. The majority of indicators in MADM models are on various scales and are frequently at odds with one another. Frequently, there is no best choice (ideally for each indicator). Furthermore, certain indications have a good and bad side to them. As a result, under a MADM model, the best choice would be subjective option A, which would offer the best value for each indicator. In the vast majority of situations, getting to A is impossible. In any event, selecting the most suited alternative will be pretty simple.

4.1.1. Using the Shannon entropy technique to calculate weight:

Step 1: The criterion option matrix is created. The qualitative values are now transformed to numeric values using the Likert scale (Table 2).

Step 2: Table 3 shows the normalization and computation of the criterion-option matrix using Equation (2) and computation p_{ij}.

Steps 3-5: Calculation of all criteria based on entropy. Table 4 combines the results of the entropy calculations, covering Steps 3 through 5. Equations (3) through (6) contain calculating equations (5). The goal values of the financial ratios are shown in step 5 by rj.

Table2. Decision matrix

Cj / Ai	Income	Social Image	Hard Work	Distance	Security
	C1	**C2**	**C3**	**C4**	**C5**
A1	15	6	3	10	6
A2	12	4	4	3	7
A3	20	7	2	30	4
A4	30	2	1	1	2

Table 3. Normalized matrix

Cj / Ai	Income	Social Image	Hard Work	Distance	Security
	C1	**C2**	**C3**	**C4**	**C5**
A1	0.1948	0.3158	0.3000	0.2273	0.1538
A2	0.1558	0.2105	0.4000	0.0682	0.0769
A3	0.2597	0.3684	0.2000	0.6818	0.3077
A4	0.3896	0.1053	0.1000	0.0227	0.4615

4.1.2. Calculation of weight using the proposed method (DWM):

Step 1: The criterion-option matrix is constructed in the same manner as the Shannon entropy technique.

Steps 2-5: Data mean, standard deviation, and coefficient of standard deviation of data were calculated, followed by the weight indicated in Table 5 of the findings.

Example 4. 2.

The data in this section is based on examples from four major global container shipping firms that rank among the top 20 worldwide: Evergreen Shipping Company, Yang Ming Shipping Company, Hanjin Shipping Company, and Hyundai Merchant Marine Company.

Table 4. Entropy calculation for all criteria

	Step3-lnpij					Step4		Step5
Criteria	A1	A2	A3	A4	$\sum p_{ij} * \ln p_{ij}$	eij	1-eij	wj
Income	-1.4816	-1.20397	-1.15268	-1.63576	-1.32575	0.9563	0.0437	0.06325
Social image	-2.68558	-0.91629	-1.55814	-1.8589	-1.29689	0.9355	0.0645	0.093399
Hard work	-0.38299	-1.60944	-0.99853	-1.34807	-1.27985	0.9232	0.0768	0.111198
Distance	-3.78419	-2.30259	-2.25129	-0.94261	-0.86697	0.6254	0.3746	0.542538
Security	-1.4816	-1.20397	-1.15268	-1.63576	-1.20479	0.8691	0.1309	0.189615

Table 5. DWM calculation for all criteria

	Step1				Step2	Step3	Step4	Step5
Criteria	A1	A2	A3	A4	μj	Sj	CVj	Wj
Income	15	12	20	30	19.25	6.832825	0.354952	0.124993
Social image	6	4	7	2	4.75	1.920286	0.404271	0.14236
Hard work	3	4	2	1	2.5	1.118034	0.447214	0.157482
Distance	10	3	30	1	11	11.46734	1.042486	0.367101
Security	6	7	4	2	3.25	1.920286	0.590857	0.208065

Table 6. Comparison of the results of the entropy and proposed method

Entropy weight	Rank	WBI Weight	Rank
0.06325	5	0.124993	5
0.093399	4	0.14236	4
0.111198	3	0.157482	3
0.542538	1	0.367101	1
0.189615	2	0.208065	2

3.2.1. Shannon entropy Method

Step 1: Matrix of Criteria and Options The goal of this phase is to gather the information provided in Table 7. The financial performance of the container transport firms reviewed on their official websites is shown in this table. The last column shows the financial ratio's overall performance, which will be used in the following stage.

Table 7. Performance of container shipping companies in financial ratios

Step1-performance	YM	EG	HMM	HJ	SUM
F1	120.30	110.99	55.24	98.26	384.79
F2	4.68	1.72	0.11	1.33	7.83
F3	5.28	20.04	10.73	5.10	41.14
F4	10.71	11.27	1.02	7.41	30.40
F5	13.16	13.62	1.17	10.31	38.27
F6	14.43	10.91	1.77	9.43	36.54
F7	54.18	49.93	1.16	70.46	175.73
F8	5.22	3.42	0.41	2.81	11.87
F9	1.17	0.36	0.70	0.82	3.06
F10	2.62	1.10	1.10	1.23	6.10
F11	1.85	0.68	7.66	5.82	16.01
F12	3.16	0.78	0.78	0.96	5.67
F13	251.40	237.25	216.23	1.24	706.12
F14	330.74	624.87	1.12	1035.17	1991.90
F15	71.14	32.07	4.54	5.15	112.90
F16	36.99	46.67	90.81	85.88	260.36
F17	0.63	0.53	0.09	0.14	1.40
F18	0.56	0.41	1.06	0.85	2.87
F19	0.59	0.88	988.50	6.08	996.06
F20	0.27	0.52	5.34	4.56	10.68
F21	0.21	0.34	0.84	0.82	2.21

Notes: EG Evergreen Shipping Company, YM Yang Ming Shipping Company, HJ Hanjin Shipping Company, and HMM Hyundai Merchant Marine Company

Step 2: Finding P_{ij}. The total of the normalized financial ratios computed in Table 3 is used to illustrate this phase in Table 3.

Steps 3-5: Entropy and total criterion calculation Table 9 combines the results of entropy calculations from Step 3 to Step 5. Calculation equations may be found in Equations (3) through (5). The outcomes of step 5, rj, indicate the financial ratios' goal values.

Table 8. Normalized financial ratio performance

Step1-performance	YM	EG	HMM	HJ
F1	0.313	0.288	0.144	0.255
F2	0.597	0.219	0.014	0.170
F3	0.128	0.487	0.261	0.124
F4	0.352	0.371	0.033	0.244
F5	0.344	0.356	0.031	0.270
F6	0.395	0.299	0.048	0.258
F7	0.308	0.284	0.007	0.401
F8	0.440	0.288	0.035	0.237
F9	0.382	0.119	0.230	0.269
F10	0.429	0.181	0.187	0.202
F11	0.116	0.042	0.478	0.363

F12	0.577	0.137	0.137	0.169
F13	0.356	0.336	0.306	0.002
F14	0.166	0.314	0.001	0.520
F15	0.630	0.284	0.040	0.046
F16	0.142	0.179	0.349	0.330
F17	0.451	0.382	0.066	0.101
F18	0.195	0.141	0.368	0.296
F19	0.001	0.001	0.992	0.006
F20	0.025	0.048	0.500	0.427
F21	0.095	0.154	0.380	0.370

4.2.2. Calculation of weight using the proposed method (DWM):

Step 1: The criterion-option matrix is constructed in the same manner as the Shannon entropy technique.

Steps 2-5: Data mean, standard deviation, and coefficient of standard deviation of data were calculated, followed by the weight indicated in Table 10 of the findings.

Table 9. Entropy calculation for all criteria

	Steps				Step3-lnp_{ij}		Step4	Step5
Financial ratios	YM	EG	HMM	HJ	$\sum p_{ij} * \ln p_{ij}$	eij	1-eij	wj
F1	-1.1627	-1.2433	-1.9410	-1.3651	-1.3494	0.9734	0.0266	0.0065
F2	-0.5153	-1.5164	-4.2940	-1.7748	-1.0001	0.7214	0.2789	0.0680
F3	-2.0540	-0.7194	-1.3436	-2.0887	-1.2230	0.8822	0.1178	0.0288
F4	-1.0435	-0.9927	-3.3973	-1.4116	-1.1932	0.8607	0.1393	0.0340
F5	-1.0673	-1.0332	-3.4836	-1.3111	-1.1951	0.8621	0.1379	0.0337
F6	-0.9293	-1.2085	-3.0278	-1.3544	-1.2240	0.8829	0.1171	0.0286
F7	-1.1767	-1.2582	-5.0170	-0.9140	-1.1200	0.8079	0.1921	0.0469
F8	-0.8205	-1.2438	-3.3545	-1.4414	-1.1780	0.8497	0.1503	0.0367
F9	-0.9614	-2.1324	-1.4682	-1.3139	-1.3117	0.9462	0.0538	0.0131
F10	-0.8452	-1.7084	-1.6747	-1.5994	-1.3093	0.9445	0.0555	0.0136
F11	-2.1558	-3.1601	-0.7372	-1.0125	-1.1043	0.7966	0.2034	0.0497
F12	-0.5844	-1.9878	-1.9893	-1.7792	-1.1705	0.8443	0.1557	0.0380
F13	-1.0327	-1.0907	-1.1834	-6.3482	-1.1076	0.7990	0.2010	0.0491
F14	-1.7955	-1.1593	-7.4836	-0.6545	-1.0062	0.7258	0.2742	0.0670
F15	-0.4618	-1.2585	-3.2136	-3.0880	-0.9185	0.6626	0.3374	0.0824
F16	-1.9514	-1.7190	-1.0533	-1.1091	-1.3186	0.9512	0.0488	0.0119

F17	-0.7958	-0.9626	-2.7213	-2.2917	-1.1374	0.8205	0.1795	0.0438
F18	-1.6373	-1.9572	-0.9988	-1.2177	-1.3231	0.9544	0.0456	0.0111
F19	-7.4364	-7.0372	-0.0076	-5.0982	-0.0493	0.0355	0.9645	0.2355
F20	-3.6868	-3.0303	-0.6933	-0.8517	-0.9487	0.6844	0.3156	0.0771
F21	-2.3502	-1.8726	-0.9663	-0.9930	-1.2475	0.8999	0.1001	0.0245

Table 10. DWM calculation for all criteria

Steps	Step1				Step2	Step3	Step4	Step5
Financial ratios	YM	EG	HMM	HJ	μ_j	Sj	Vcj	wj
F1	120.30	110.99	55.24	98.26	96.1975	24.90742	0.25892	0.0193
F2	4.68	1.72	0.11	1.33	1.96	1.678943	0.856604	0.0638
F3	5.28	20.04	10.73	5.10	10.2875	6.068201	0.589862	0.0439
F4	10.71	11.27	1.02	7.41	7.6025	4.076563	0.536214	0.0399
F5	13.16	13.62	1.17	10.31	9.565	5.009943	0.506162	0.0390
F6	14.43	10.91	1.77	9.43	9.135	4.623794	0.523779	0.0377
F7	54.18	49.93	1.16	70.46	43.9325	25.85622	0.588544	0.0438
F8	5.22	3.42	0.41	2.81	2.965	1.720763	0.580358	0.0432
F9	1.17	0.36	0.70	0.82	0.7625	0.289515	0.379691	0.0283
F10	2.62	1.10	1.14	1.23	1.5225	0.635389	0.417332	0.0311
F11	1.85	0.68	7.66	5.82	4.0025	2.843979	0.710551	0.0529
F12	3.16	0.78	0.78	0.96	1.42	1.007274	0.709348	0.0528
F13	251.40	237.25	216.23	1.24	176.53	101.9744	0.57766	0.0430
F14	330.74	624.87	1.12	1035.17	497.975	380.6288	0.764353	0.0569
F15	71.14	32.07	4.54	5.15	28.225	27.15657	0.962146	0.0716
F16	36.99	46.67	90.81	85.88	65.0875	23.57249	0.362166	0.0270
F17	0.63	0.53	0.09	0.14	0.3475	0.235836	0.678666	0.0505
F18	0.56	0.41	1.06	0.85	0.72	0.252091	0.350127	0.0261
F19	0.59	0.88	988.50	6.08	249.0125	426.9489	1.714568	0.1276
F20	0.27	0.52	5.34	4.56	2.6725	2.295837	0.85906	0.0639
F21	0.21	0.34	0.84	0.82	0.5525	0.281369	0.509266	0.0379

4.3. Comparing results:

Table 11. Comparison of the results of the entropy and proposed method

Methods	Entropy Method		Proposed Method	
Financial ratios	wj	rank	wj	rank
F1	0.0065	21	0.019271	21
F2	0.0680	4	0.063757	4
F3	0.0288	14	0.043904	9
F4	0.0340	12	0.039911	13
F5	0.0337	13	0.038985	14
F6	0.0286	15	0.037674	15
F7	0.0469	8	0.043806	10
F8	0.0367	11	0.043196	11
F9	0.0131	18	0.028261	18
F10	0.0136	17	0.031062	17
F11	0.0497	6	0.052887	6
F12	0.0380	10	0.052797	10
F13	0.0491	7	0.042995	7
F14	0.0670	5	0.056891	5
F15	0.0824	2	0.071613	2
F16	0.0119	19	0.026956	19
F17	0.0438	9	0.050513	8
F18	0.0111	20	0.02606	20
F19	0.2355	1	0.127616	1
F20	0.0771	3	0.06394	3
F21	0.0245	16	0.037905	16

Two numerical examples were provided in this section, and the weights of the criterion were determined using the two weighing methods stated previously (Shannon entropy and the proposed method). Tables 6 and 11 present the findings. The results of both weighting systems were strongly linked in the example 4. 1 and example 4.2. Figure 1,2 illustrate this.

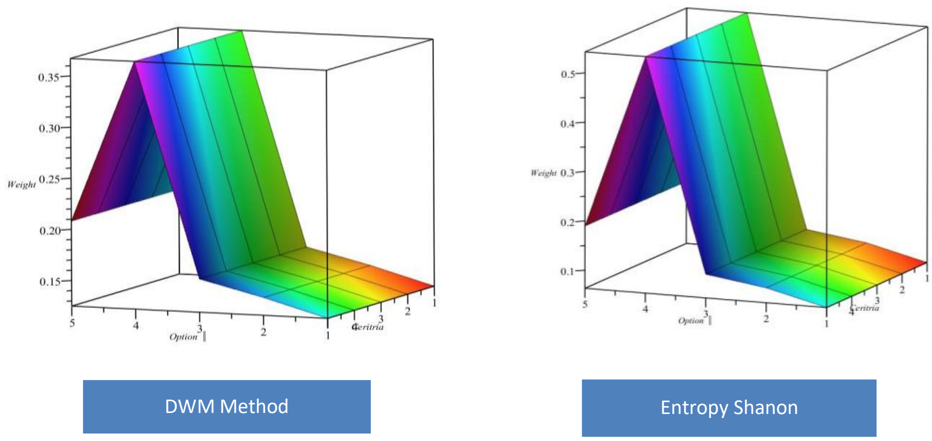

Fig1. Comparison of Shannon entropy and DWM results for the example 4. 1

All values and rankings of the criterion were the same in the first example with four possibilities, and all values and rankings of the criteria were the same in the second example with 22 options except for 5, which was the same in both ways. The Pearson correlation coefficient was used to assess the relationship intensity, kind of relationship (direct or inverse), and weight using both techniques to evaluate the effectiveness of the DWM. This coefficient ranges from 1 to -1, and it will be equal to

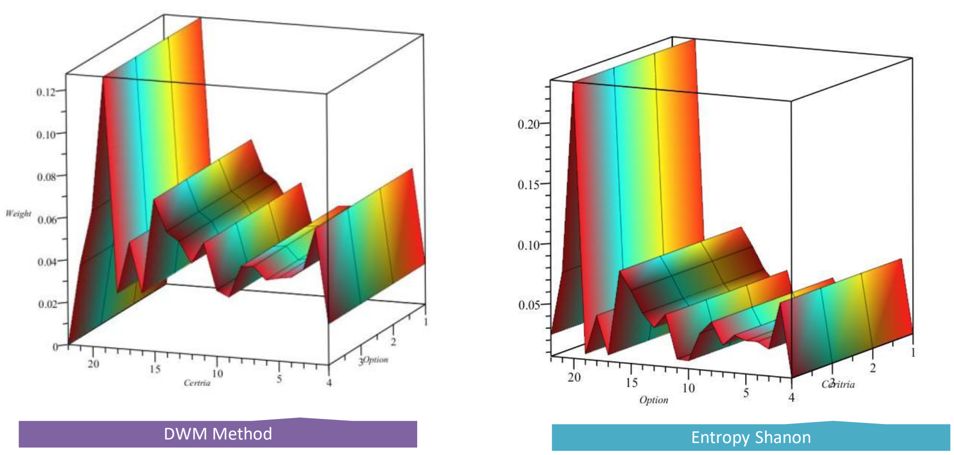

Fig2. Comparison of Shannon entropy and DWM results for the example ٤. 2

zero if there is no link between the two variables. The correlation rate between the values produced by weighting by entropy technique and the suggested method (DWM) was calculated using SPSS software and found to be 0.997 in the first case and 0.979 in the second. This demonstrates a high level of connection. The correlation coefficient was calculated using SPSS software. Figure 3 shows a comparison of the outcomes of both approaches for the second case.

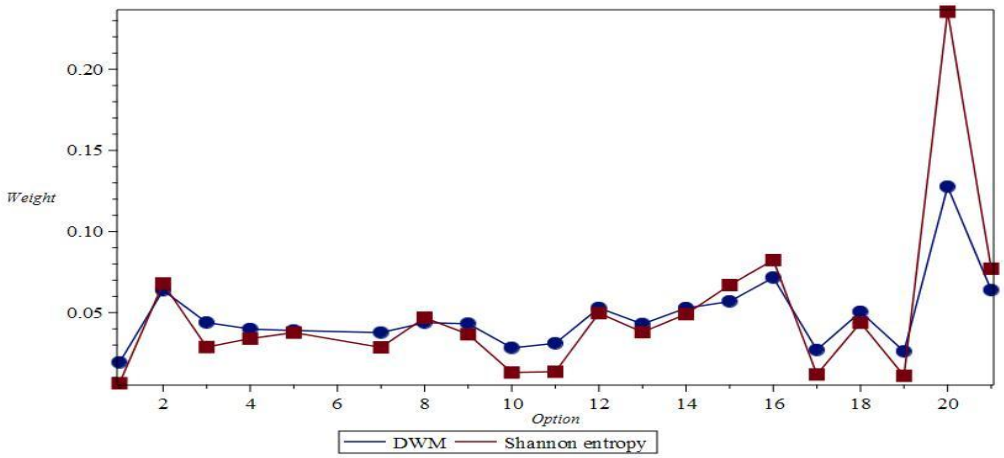

Fig 3: Comparison of Shannon entropy and DWM results for the example 4.2.

5. Managerial Insights

The proposed dispersion-based weighting method (DWM) provides several practical advantages for managers and decision-makers operating in multi-criteria environments. By relying on simple statistical dispersion measures, the method enables the objective and transparent determination of criteria weights without requiring complex mathematical transformations. This simplicity enhances its applicability in real-world managerial contexts where interpretability, efficiency, and ease of implementation are essential.

Another important advantage of DWM is its ability to operate directly on raw data. Unlike many traditional objective weighting methods, the proposed approach does not require data normalization and can handle decision matrices containing negative values. This flexibility makes it applicable to a wide range of managerial decision problems such as financial evaluation, supplier selection, risk assessment, and strategic performance analysis.

From a managerial standpoint, DWM improves the reliability of decision outcomes by assigning greater importance to criteria with higher informational dispersion, thereby helping decision-makers focus on factors that better distinguish among alternatives. Consequently, the method can support more effective prioritization, resource allocation, and strategic decision-making. Overall, the simplicity, flexibility, and analytical reliability of DWM make it a practical tool for enhancing decision quality in both public and private sector applications.

6. Conclusion

This study introduced a new dispersion-based weighting method (DWM) as an objective and statistically grounded approach for determining criterion weights in multi-criteria decision-making (MCDM). By relying solely on the mean, standard deviation, and coefficient of variation of the decision matrix, the method provides a simple yet effective five-step framework that captures the intrinsic variability of each criterion without the need for data transformation. To evaluate its performance, DWM was compared with the widely applied Shannon entropy method through two numerical examples. The results showed a remarkably high level of consistency between the two approaches, with Pearson correlation coefficients of 0.997 and 0.979. In the first example, the two methods produced identical weight values and rankings, while in the second example, only one criterion exhibited a slight deviation. These findings confirm both the robustness and the practical credibility of the proposed method.

Beyond consistency, the analysis highlights several important advantages of DWM relative to Shannon entropy. First, DWM eliminates the need for normalization of the decision matrix, thereby simplifying the preprocessing stage and preventing potential distortions caused by normalization procedures. Second, while Shannon entropy cannot be directly applied when the decision matrix contains negative values, DWM accommodates negative data naturally and without modification. Third, the computational structure of DWM is straightforward and based exclusively on basic statistical calculations, whereas Shannon entropy requires logarithmic operations that increase both computational complexity and the risk of numerical instability near zero. Taken together, these strengths establish DWM as a flexible, efficient, and broadly applicable alternative for objective weight determination.

Despite its advantages, several limitations must be acknowledged. The empirical assessment of DWM was based on a limited number of numerical examples, which may not fully reflect the variety and complexity of real-world MCDM problems. Additionally, because the method is purely objective and relies only on dispersion measures, it does not incorporate expert judgment or contextual preferences that may play an essential role in certain decision environments. The behavior of the method in the presence of highly skewed, noisy, or extreme-valued datasets also remains to be systematically investigated.

These considerations highlight promising avenues for future research. Extending the evaluation of DWM to large-scale, high-dimensional, or domain-specific datasets would strengthen empirical validation and provide deeper insights into its performance across different contexts. Integrating DWM into established MCDM techniques such as TOPSIS, VIKOR, EDAS, or MARCOS would help assess how the proposed weighting scheme influences alternative rankings in diverse decision-making scenarios. Furthermore, studying the sensitivity of DWM to outliers or extreme dispersion patterns, and developing fuzzy, interval-based, or robust variants of the method, could expand its applicability to more complex and uncertain environments.

Overall, DWM offers a valuable contribution to the field of objective weighting in MCDM by presenting a computationally simple, normalization-free, and data-flexible method that maintains strong consistency with the Shannon entropy approach while overcoming several of its inherent limitations. These characteristics enhance its potential for adoption in both academic research and real-world decision-making applications.

References

[1] Alinezhad, A., & Khalili, J. (2019). *CRITIC method.* In *New Methods and Applications in Multiple Attribute Decision Making (MADM)* (pp. 199–203). Springer.

[2] Almonte, G. J. C., Soriano, P. I. R., & Promentilla, M. A. B. (2026). *Energy security, equity, and sustainability: A multi-criteria decision analysis framework for nuclear power evaluation in emerging economies. Energy*, 140971.

[3] Andargoli, S. M., Arasteh, A., & Divsalar, A. (2025). *A hybrid Bayesian BWM–fuzzy MARCOS–metaheuristic framework for sustainable smart locker location in last-mile urban logistics. Iranian Journal of Operations Research*, 16(2), 1–25.

[4] Anderson, E., Crosby, D., & Ussher, G. (2000). *Bulls-eye! Simple resistivity imaging to reliably locate the geothermal reservoir.* In *Proceedings of the World Geothermal Congress.*

[5] Bezdan, A., et al. (2025). *An objective methodology for waterlogging risk assessment based on the entropy weighting method and machine learning. Catena*, 249, 108618.

[6] Chen, M., et al. (2025). *Mapping groundwater potential zones in mountainous areas of Southern China using GIS, AHP, and fuzzy AHP. Scientific Reports*, 15(1), 17159.

[7] Dağıdır, B. D., & Özkan, B. (2024). *A comprehensive evaluation of company performance using sustainability balanced scorecard based on picture fuzzy AHP. Journal of Cleaner Production*, 435, 140519.

[8] Darko, A., et al. (2019). *Review of application of analytic hierarchy process (AHP) in construction. International Journal of Construction Management*, 19(5), 436–452.

[9] Dwivedi, P. P., & Sharma, D. K. (2026). *Comparative assessment of flexible manufacturing systems using the EDAS and Shannon entropy method. Croatian Operational Research Review*, 17(1), 1–17.

[10] Elanda, R. W., Simbolon, O., & Ikhsan, W. L. (2026). *Pembobotan kriteria evaluasi kinerja pemasok dengan mempertimbangkan risiko gangguan menggunakan metode Best Worst Method. Jurnal Serambi Engineering*, 11(1).

[11] Fetic, M., Khattak, A., & Jovcic, S. (2026). *An intelligent decision framework for optimizing sustainable last-mile delivery: Parcel locker location with IMF SWARA–WASPAS. Journal of Intelligent Management and Decisions*, 5(1), 1–10.

[12] Gülmez, B. (2026). *Banana drying method selection: A hybrid multi-criteria decision making approach integrating SWARA weighting with MOORA, MARCOS, and PSI ranking methods. Journal of Food Processing and Preservation*, 2026(1), 1973243.

[13] Gupta, P., et al. (2026). *A picture fuzzy numbers–based AHP–CoCoSo approach.* In *Reliability Modelling, System Engineering, and Management through Computational Intelligence* (p. 87).

[14] Haktanır, E., & Kahraman, C. (2022). *A novel picture fuzzy CRITIC & REGIME methodology: Wearable health technology application. Engineering Applications of Artificial Intelligence*, 113, 104942.

[15] Hosseinzadeh Lotfi, F., et al. (2023). *The criteria importance through inter-criteria correlation (CRITIC) in uncertainty environment.* In *Fuzzy Decision Analysis: Multi-Attribute Decision Making Approach* (pp. 309–324). Springer.

[16] Jessop, A. (2014). *IMP: A decision aid for multi-attribute evaluation using imprecise weight estimates. Omega*, 49, 18–29.

[17] Kamfiroozi, M. H., & Naeini, A. B. (2013). *Supplier selection in grey environment: A grey, AHP, bulls-eye and ELECTRE approach. International Journal of Information, Security and Systems Management*, 2(1), 110–116.

[18] Kumar, N., et al. (2026). *An integrated IVN–AHP–CODAS framework for enhancing cold supply chain performance through Industry 4.0. Journal of Industrial Integration and Management.*

[19] Kumar, N., Dixit, A., & Vijay, V. (2025). *Entropy measures and their applications: A comprehensive review. arXiv preprint arXiv:2503.15660.*

[20] Kumar, R. (2025). *A comprehensive review of MCDM methods, applications, and emerging trends. Decision Making Advances*, 3(1), 185–199.

[21] Kumar, V., Saxena, P., & Garg, H. (2026). *Selection of optimal software reliability growth models using an integrated entropy–TOPSIS approach. Mathematical Methods in the Applied Sciences*, 49(5), 3475–3495.

[22] Li, J. (2026). *Optimizing multidimensional decision-making for sustainable agricultural models: Establishing an evaluation system based on dynamic entropy weight method and Monte Carlo validation. Journal of Computer Science and Frontier Technologies*, 2(2), 59–71.

[23] Liao, J., et al. (2026). *An entropy-based multi-criteria approach for intensity measure selection in seismic resilience of structures. Resilient Cities and Structures*, 5(1), 1–13.

[24] Madanchian, M., & Taherdoost, H. (2025). *Applications of multi-criteria decision making in information systems for strategic and operational decisions. Computers*, 14(6), 208.

[25] Majeed, R. A., & Breesam, H. K. (2021). *Application of SWARA technique to find criteria weights for selecting landfill site in Baghdad governorate. IOP Conference Series: Materials Science and Engineering.* IOP Publishing.

[26] Nadeem, R., et al. (2025). *Prioritizing determinants of employees' green behavior in the Indian hotel industry: An analytic hierarchy process (AHP) and fuzzy AHP approach. Journal of Hospitality and Tourism Insights.*

[27] Nalina, M., et al. (2026). *Integrating subjective–objective weighting with multi-criteria decision models for sustainable masonry material selection. Innovative Infrastructure Solutions*, 11(4), 160.

[28] Naziro, K., Perdana, Y. R., & Kristanto, D. (2025). *Supply chain performance measurement and determination of improvement priorities using SCOR–DS and ANP methods: Case study on waste management. Journal of Industrial Engineering and Halal Industries*, 6(1), 81–88.

[29] Nguyen, V., & Chaysiri, R. (2025). *CRITIC–CoCoSo model application in hybrid solar–wind energy plant location selection problem: A case study in Vietnam. Energy Engineering: Journal of the Association of Energy Engineers*, 122(2), 515.

[30] Paji, A. G., Amiri, A. B., & Moghaddam, R. T. (2024). *Integrated multi-model risk assessment of an aging gas pipeline using fuzzy AHP and 3D uncertainty matrix. Iranian Journal of Operations Research*, 15(2), 99–121.

[31] Palanikumar, M., & Kausar, N. (2027). *Redefined square root interval-valued normal Pythagorean fuzzy multi-attribute decision-making model based on aggregation operators. Spectrum of Operational Research*, 1–18.

[32] Pandey, N., Dash, S. P., & Kaur, P. (2026). *A systematic review of multi-criteria decision-making (MCDM) methods applied to personnel selection: Trends, models, and effectiveness. OPSEARCH*, 1–59.

[33] Pantović, D., et al. (2026). *Assessing disparities in climate and energy agri-environmental indicators among EU countries using the PROMETHEE–GAIA method and the entropy index. Agriculture*, 16(4), 463.

[34] Paradowski, B., Wątróbski, J., & Sałabun, W. (2025). *Novel coefficients for improved robustness in multi-criteria decision analysis. Artificial Intelligence Review*, 58(10), 298.

[35] Peng, H.-G., Wang, X.-K., & Wang, J.-Q. (2022). *New MULTIMOORA and pairwise evaluation-based MCDM methods for hotel selection based on Z-numbers. International Journal of Fuzzy Systems*, 24(1), 371–390.

[36] Peng, J. J., et al. (2024). *A heterogeneous picture fuzzy SWARA–MARCOS evaluation framework based on a novel cross-entropy measure. International Journal of Systems Science*, 55(8), 1528–1552.

[37] Rezaei, J. (2015). *Best–worst multi-criteria decision-making method. Omega*, 53, 49–57.

[38] Rezaei, J. (2026). *Best–Worst Method: A decade of evolution and future prospects. Omega*, 103546.

[39] Rokhsari, S., & Sadeghi-Niaraki, A. (2015). *Urban network risk assessment using fuzzy-AHP and TOPSIS in GIS environment. Iranian Journal of Operations Research*, 6(2), 73–86.

[40] Roszkowska, E. (2026). *Entropy and normalization in MCDA: A data-driven perspective on ranking stability. Entropy*, 28(1), 114.

[41] Saaty, T. L., & Vargas, L. G. (2013). *The analytic network process.* In *Decision Making with the Analytic Network Process* (pp. 1–40). Springer.

[42] Sahoo, S. K., Choudhury, B. B., & Dhal, P. R. (2027). *A comprehensive review of fuzzy multiple criteria decision-making (MCDM) methods: Advancements, applications, and future directions. Spectrum of Decision Making and Applications.*

[43] Shafaei, A., et al. (2025). *An integrated decision-making approach for identifying sustainable tier-1 suppliers: Fuzzy Delphi–Borda–SWARA. Annals of Operations Research*, 1–38.

[44] Tao, X., et al. (2026). *Evaluation of cognitive load of industrial control interface by integrating dynamic weights and improved GRA–TOPSIS. International Journal of Human–Computer Interaction*, 1–28.

[45] Thakkar, J. J. (2021). *Stepwise weight assessment ratio analysis (SWARA).* In *Multi-Criteria Decision Making* (pp. 281–289). Springer.

[46] Thomas, B. C., et al. (2004). *Quantifying the bull's-eye effect. The Astrophysical Journal*, 601(1), 28–36.

[47] Topaloğlu, F. (2025). *Analytic network process (ANP)-based decision support tool for nuclear power plant location and reactor type selection. Nuclear Engineering and Technology*, 57(3), 103228.

[48] Xu, X. (2001). *The SIR method: A superiority and inferiority ranking method for multiple criteria decision making. European Journal of Operational Research*, 131(3), 587–602.

[49] Zhu, Y., Tian, D., & Yan, F. (2020). *Effectiveness of entropy weight method in decision making. Mathematical Problems in Engineering*, 2020(1), 3564835.