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A Robust Decision-Making Model for Medical Supplies via Selecting Appropriate Unmanned Aerial Vehicle

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Abstract: Recently, Unmanned Aerial Vehicles (UAVs) have been used in many fields, including the field of health care, especially in delivering the necessary medical equipment and supplies, due to the many advantages they have compared to other traditional methods and the presence of different types of UAVs, to improve healthcare and provide it with the medical supplies and equipment necessary to save the lives of patients. Choosing the appropriate UAV for a specific situation represents a problem facing decision-makers, which is considered a multi-criteria decision-making problem. Since the decision-making process is cumbersome and complex, and deals with uncertainty and ambiguity. In this research, we proposed multi-criteria decision-making (MCDM) model using CRITERIA (Criteria Importance through Intercriteria Correlation) and MARICA (Multi-Attribute Rating Analysis with Ideal Concepts) methods integrated with neutrosophic logic, which is considered a powerful tool in dealing with uncertainty and ambiguity. The CRITIC method calculates the weight of criteria, whereas it takes into account the correlations and relationships between the criteria, whether they are positive or negative, unlike other methods that consider the criteria separately, which allows for a more accurate and comprehensive analysis of the decision problem. The MARICA method is used also to rank the alternatives. It allows decision-makers to evaluate alternatives according to how well they perform across multiple criteria by considering several factors at once. This helps increase the effectiveness of judgments by taking into account all relevant factors. Moreover, MARICA is a user-friendly method that doesn't require complex mathematical calculations, making it accessible to anyone who wants to make sound choices. The UAV with the highest ranking is the one that will be chosen and represents the best among the alternatives. The proposed model proved its effectiveness by applying it to an experimental case.

Keywords: Unmanned Aerial Vehicle; MCDM; CRITIC; MARICA; Medical Supplies Delivery.

1. Introduction

Healthcare is crucial in saving human lives, and its demand has recently surged. Delivering medical supplies efficiently and reliably has become more important than ever, particularly after the outbreak of the coronavirus pandemic. This includes delivering necessary equipment and supplies to patients to provide them with the healthcare they need. Timely delivery of medical supplies is critical to saving lives, and traditional transportation and delivery operations often face obstacles in terms of delivering the package late or some damage, such as breakage and corruption, Therefore, a solution must be sought.

With the spread of information technology and the Internet of Things (IoT), which has contributed to the development of health care [1], unmanned aircraft systems have been included in the development of transportation and delivery operations, especially in urban areas, due to their characteristics [2]. UAVs have proven to be a highly versatile tool across various industries, playing a crucial role in addressing several pressing issues, it was used in agriculture [3], was used in animal wealth, as it contributed to the effective detection of and counting of livestock [4], was used in water management [5]. Similarly, in the medical field, UAVs have brought about a significant breakthrough in delivering medical equipment to remote areas that are difficult to access through conventional means. This has been instrumental in ensuring that medical aid reaches those in need in a timely and efficient manner [6]. UAVs are increasingly being recognized as a viable option for delivering medical resources and equipment. They offer several advantages over traditional delivery methods, such as their high speed, ease of deployment, and ability to access remote areas that are difficult to reach otherwise [7-9]. Additionally, drones are highly resistant to wind, making them suitable for delivering packages even in challenging weather conditions while ensuring the safety of the items being transported [10]. The authors discussed the limitations of prehospital blood transfusion in military settings, and the potential uses of UAVs for medical logistics [11]. Comparisons were made and it was proven that using UAVs to transport medical supplies to healthcare facilities is more cost-effective and environmentally friendly than using traditional techniques has been demonstrated [12].

Because there is a wide range of UAVs on the market, each with its own set of features, choosing the best UAV type to meet a given situation can be difficult and restrictive for decision-makers, they all have distinct goals and perspectives. To select the finest one, a methodical approach is therefore required between options based on the applied criteria. Therefore, choosing and evaluating UAVs and using them in the process of delivering medical supplies represents a challenge for multi-criteria decision-making.

MCDM is a technique that involves analyzing the various available options in a situation and has been used to choose the best UAV to be used to deliver medical supplies and equipment. Some authors aimed to highlight the evolution and significance of MCDM approaches in military healthcare by examining the literature's different applications of MCDM methods in the military and healthcare domains [13]. The interval-valued Pythagorean fuzzy VIKOR approach and the interval-valued Pythagorean fuzzy analytic hierarchy process were used to select UAVs for transporting medical supplies between disaster zones and warehouses [14]. The authors provided a comprehensive set of criteria for comparing various last-mile drone options, which used the interval-valued inferential fuzzy TOPSIS method which is a systematic decision-making strategy and handling uncertainty [15].

The aforementioned studies have demonstrated that utilizing MCDM technology enables one to arrive at informed decisions. Therefore, in this research we present a method to evaluate UAVs and choose the best among the alternatives, which are used in the operations of delivering and supplying medical supplies, using a new MCDM model in the context of neutrosophic logic.

This research aims to help decision-makers make the best decision based on an organized and effective methodology based on expert's opinions. Therefore, to select the best UAV for medical supply delivery, the problem was formulated as a MCDM problem.

Utilizing MCDM technology to evaluate the best UAV suitable for delivering the necessary medical supplies through:

- Applying the CRITIC (Criteria Importance Through Intercriteria Correlation) method, to calculate the weight of criteria and sub-criteria related to UAVs used for delivering medical supplies.
- Applying the MARICA (Multi-Attribute Rating Analysis with Ideal Concepts) method for ranking the alternatives depending on the weight calculated by CRITIC, this is in the context of the concept of truth, falsity, and indeterminacy (T,I, and$F$) membership.

Also, the proposed method to evaluate the best UAV is simple and has the great ability to deal with uncertainty phenomena and solve the ambiguous information that commonly arises in the decision-making process.

The remaining parts of our research are provided below for processing purposes. In section 2, a proposed methodology for selecting the best UAV among the alternatives that are used in medical supply delivery is described. In section 3, a case study for selecting the best UAV is solved to demonstrate the method's applicability in a neutrosophic environment. In section 4, the managerial implications are presented. This research's conclusions and recommendations for the future are presented in Section 5.

2. Methodology

Our model utilizes two MCDM techniques for selecting the best UAV among the alternatives that are used in medical supply delivery. We are using the CRITIC as an MCDM method to get weights of criteria, and we are using the MARICA method to rank the UAV according to the weights that are obtained from the CRITIC. Figure 1 shows, the flowchart of our model. Our model consisted of several steps as follows:

Step 1: (Define the experts based on the area of concern): Experts are people with great experience and have high knowledge in the field of UAV devices.

Step 2: Determined list of evaluation (criteria and sub-criteria) and alternatives based on expert opinions, let C be a set of criteria$C = \{c1, c2 \ldots\ldots cn\}$, where $c1, c2 \ldots\ldots cn$ are main criteria in each criteria Ci, $1 < i < n$ is formed by sub-criteria: $C1 = \{c11, c12 \ldots.\}$, $C2 = \{c21, c22 \ldots.\}$. Let's consider $A = \{A_1, A_2, A_3, A_4\}$ be a set of alternatives representing the UAV's type.

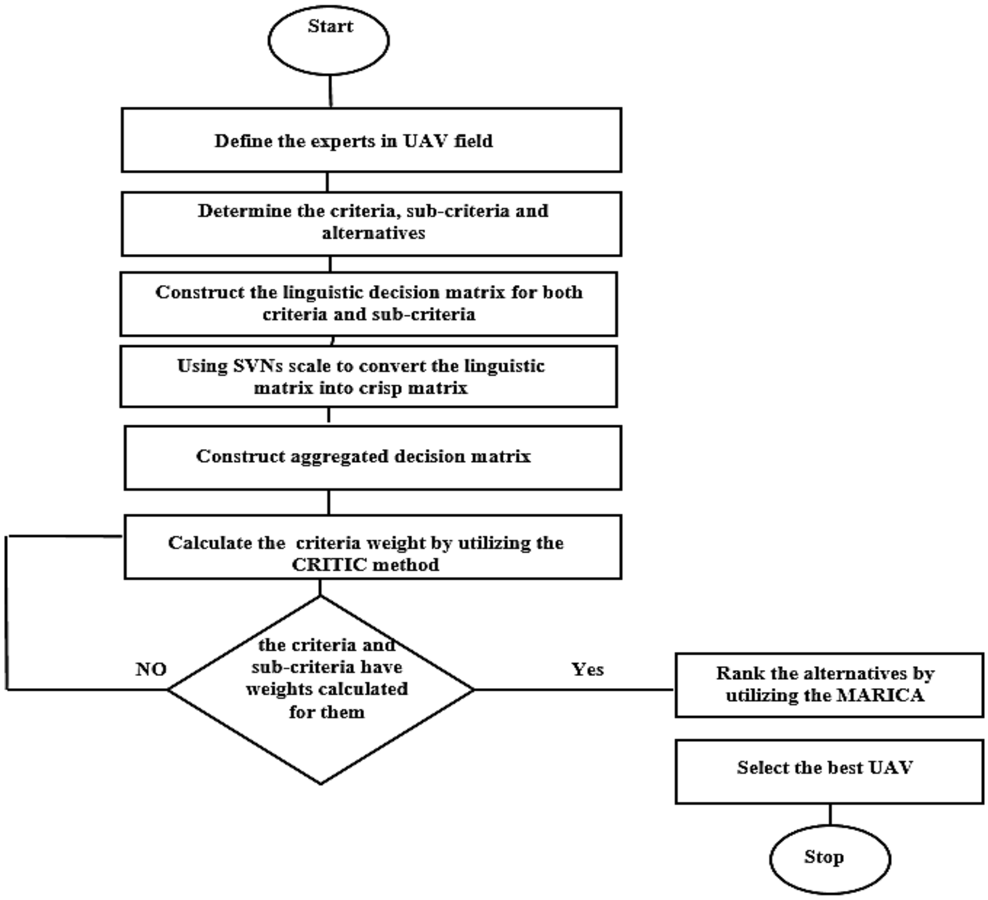

Figure 1. The flowchart of our model.

Step 3: (Expert decision matrix): When making decisions, we often encounter ambiguity, as all decisions usually involve uncertain or unclear information. However, simply using linguistic variables to address uncertainty is not enough. To tackle the problem of linguistic ambiguity, we propose the use of the neutrosophic group which is capable of dealing with the ambiguous information that commonly arises in the decision-making process. Thus, we use a single-valued neutrosophic scale (SVNs) to convert the linguistic scale into a corresponding numerical scale, using the terms used by experts to construct decision matrices. Each term used by experts has a set of characteristics including truth, indeterminacy, and falsity, collectively referred to as SVNS. As shown in Table 1. After collecting the SVNS data, it can be converted into a distinct value that is compatible with the proposed model. It is important to note that the neutrosophic matrix can be transformed into a crisp matrix using the scoring function represented in Eq. (1) [16].

$$Score\ Function = \frac{2+(Tr-F-Id)}{3} \tag{1}$$

Where Tr, F, Id refers to truth, false, and indeterminacy respectively.

Step 4: (Construct aggregated decision matrix): Because we have more than one expert and each of them has its decision matrix, the experts' matrices must be collected into one decision matrix called aggregated decision matrix by using Eq. (2).

$$Y_{ij} = \frac{\sum_{j=1}^{N} g_{ij}}{N} \tag{2}$$

Where g_{ij} represents the value of criterion in the matrix, N represents the number of experts.

Step 5: (CRITIC method): To determine criteria weights of relative importance. Where, the standard deviation score is used to measure the degree of variety and dispute, and determines the relationship between each attribute using the correlation coefficient between them. The CRITIC method was introduced by Diakoulaki in 1995 and can be summarized into the following steps [17].

Step 5.1: Normalized aggregated decision matrix by applying Eq. (3) as follows:

$$x_{ij}^{-} = \frac{x_{ij} - x_{worst}}{x_{best} - x_{worst}} \quad , i = 1,2 \dots . m , j = 1,2 \dots n \tag{3}$$

Where, x_{ij}^{-} is the normalized performance score of ith alternative on jth criteria, x_{worst} is the worst score of criteria j and the x_{best} is the best score of criteria j, where m is the number of alternatives and n is the number of criteria.

Step 5.2: Calculate the standard division of each criteria by applying Eq. (4) as follows:

$$\sigma_j = \sqrt{\frac{(\sum_{i=1}^{m} x_{ij} - x_j^{-})^{\wedge}2}{m-1}} \tag{4}$$

Where x_j^{-} the mean score of the criterion is j calculated from Eq. (3), and m is the number of alternatives.

Step 5.3: Determine the symmetric matrix of $n * n$ with the element r_{jk}, which is the linear correlation coefficient between the vector x_j and x_k , It can be seen that the more discordant the scores of the alternatives in criteria j and k, the lower the value r_{ik}.

Step 5.4: Calculate the measure of the conflict created by criterion j with respect to the decision situation defined by the rest of the criteria, by applying Eq. (5) as follows:

$$Con = \sum_{k=1}^{m} (1 - r_{jk}) \tag{5}$$

Step 5.5: Determine the quantity of the information in relation to each criterion, by applying Eq. (6) as follows:

$$C_j = \sigma_j * \sum_{k=1}^{m} (1 - r_{jk}) \tag{6}$$

Step 5.6: Determine the criteria weights by applying Eq. (7) as follows:

$$w_j = \frac{C_j}{\sum_{k=1}^{m} C_j} \tag{7}$$

Step 6: (MARICA method): We utilize the MARICA method to rank the alternatives, the MARICA method was introduced by Pamucar et al in 2014 [18]. By the MARICA method, the overall gap for each alternative is calculated by summing the gaps for each criterion, After that, the alternatives are ranked, and the alternative with the lowest value of the total gap is the best alternative that will be chosen, where, the alternative with the smallest overall gap is the one that has the most similar values to the ideal values of the criterion across the greatest number of criteria. The MARICA is implemented through the following:

Step 6.1: Calculating decision matrix, we used the aggregated matrix that we calculated before in step 4 as the decision matrix for the MARICA method.
Step 6.2: Establishment of preferences according to alternatives p_{Ai} choice.

$$p_{A_i} = \frac{1}{m} \; ; \; \sum_{i=1}^{m} p_{A_i} = 1 \quad , i = 1,2 \ldots m \tag{8}$$

Where m is the total number of alternatives, take into account that all preferences of the individual alternatives are equal:

$$p_{A_1} = p_{A_2} = \cdots p_{A_m} \tag{9}$$

Step 6.3: Calculation of the matrix element of theoretical evaluation T_p with size $(n \; x \; 1)$ as follows:

$$T_p = p_{A_i} \left[p_{A_1} * w_1 \quad p_{A_2} * w_2 \quad \ldots \quad p_{A_i} * w_n \right] \tag{10}$$

Where n is the number of criteria and w_n is the criteria weight coefficients that we calculated before by CRITIC method.
Step 6.4: Calculation of the actual evaluation matrix T_r as follows:

$$T_r = \begin{array}{c} A_1 \\ A_2 \\ A_m \end{array} \begin{bmatrix} t_{r11} & \ldots & t_{r1n} \\ \vdots & \ldots & t_{r2n} \\ t_{rm1} & \ldots & t_{rmn} \end{bmatrix} \tag{11}$$

Where n is the number of criteria and m is the number of alternatives. The T_r is determined by multiplying the matrix elements of the theoretical evaluation T_p and the elements of the initial decision matrix (X) according to the expression:

- For criteria of (benefit type):

$$t_{rij} = t_{pij} \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \right) \tag{12}$$

- For criteria of (non-benefit type):

$$t_{rij} = t_{pij} \left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \right) \tag{13}$$

Step 6.5: Calculation of the total gap matrix (G): the elements of the matrix are obtained as the difference (gab) between the t_{rij} and the t_{pij}

$$G = \begin{bmatrix} t_{p11} - t_{r11} & \ldots & t_{p1n} - t_{r1n} \\ \vdots & \ldots & t_{p2n} - t_{r2n} \\ t_{pm1} - t_{rm1} & \ldots & t_{pmn} - t_{rmn} \end{bmatrix} \tag{14}$$

Step 6.6: Calculation of the final value of criterion functions (Q_i) by alternatives, calculated as follows:

$$Q_i = \sum_{j=1}^{n} g_{ij} \quad , i = 1,2 \ldots . m \tag{15}$$

Step 6.7: Ranking of the alternatives.

Table 1. Single-valued neutrosophic scale (SVNs) [16].

Variables of Linguistic	**Abbreviation**	**SVNs**		
		Tr	**Id**	**F**
Extremely Bad	EB	0.00	1.00	1.00
Very Very Bad	VVB	0.10	0.90	0.90
Very Bad	VB	0.20	0.85	0.80
Bad	B	0.30	0.75	0.70
Medium Bad	MB	0.40	0.65	0.60
Medium	M	0.50	0.50	0.50
Medium Good	MG	0.60	0.35	0.40
Good	G	0.70	0.25	0.30
Very Good	VG	0.80	0.15	0.20
Very Very Good	VVG	0.90	0.10	0.10
Extremely Good	EG	1.00	0.00	0.00

3. Case Study (Result and Analysis)

In our study, We will conduct an experiment study to evaluate our proposed model to choose the best UAV to deliver medical equipment, as there is a need to deliver the ICD device and blood bags from Dr. Magdy Yacoub Hospital in Aswan City to Dar Al Fouad Hospital in Cairo city to perform a heart surgery necessary to save a patient's life. This device is small in size, and the distance between Aswan and Cairo is about 906 kilometers, which takes an arrival time of about 11 hours using traditional methods. Thus, the UAV is used to transport the ICD device and the necessary blood bags to Dar Al Fouad Hospital in Cairo instead of traditional methods, due to the importance of time and the safe arrival of the package. Therefore the selection of suitable UAVs is a hard task.

We are introducing a new method to assist decision-makers in selecting the most appropriate UAV from a set of UAVs for delivering medical supplies taking into account factors such as time and package delivery integrity. We assume that there are four UAVs (alternatives), each with unique characteristics (criteria) that are denoted as $A = \{A_1, A_2, A_3, A_4\}$ and that there are four decision-makers with extensive knowledge of a particular subject.

Step 1: We assume that there are four experts $\{expert1, expert2,\ expert3$, and $expert4\}$ as follows: Expert1&2: have a PhD degree in the aeronautical engineering field. Expert 3: have a PhD degree in the medical field. Expert 4: have a PhD degree in the machine learning field. The expert who possesses extensive experience and high knowledge in designing, operating, and maintaining UAVs. All of them have the same level of expertise. The experts will evaluate the judgment comparison of the main criteria based on their area of concern.

Step 2: The selection of a UAV involves assessing the importance of various criteria, which differ from one alternative to another. Hence, it is crucial to determine and define the criteria to be used in medical supply delivery. In this research, we will outline criteria that are collected from previous research [19, 20]. In this research, we divide criteria into main criteria and others branching from them(sub-criteria), three main criteria $\{\mathrm{C1}, \mathrm{C2}, \mathrm{C3}\}$ that have been defined for choosing the best UAV for medical supply delivery, and each of them includes sub-criteria {payload, speed, distance, control system, safety, Clock synchronization and flight time} which denoted as $\{\mathrm{C11}, \mathrm{C12}, \mathrm{C13}, \mathrm{C21}, \mathrm{C22}, \mathrm{C31}, \mathrm{C32}\}$ respectively, as shown in Table 2. The criteria and sub-criteria described as follows: the main criteria= $\{\mathrm{C1}, \mathrm{C2}, \mathrm{C3}\}$, where $\mathrm{C1}$ = performance, $\mathrm{C2}$ = physical feature and $\mathrm{C3} =$ timing. The sub-criteria $\mathrm{C1} = \{\mathrm{C11}, \mathrm{C12}, \mathrm{C13}\}$ = {payload, speed, distance}, $\mathrm{C2} = \{\mathrm{C21}, \mathrm{C22}\}$ = {control system, safety} and $\mathrm{C3} = \{\mathrm{C31}, \mathrm{C32}\}$= {Clock synchronization, flight time}. The performance criterion $(\mathrm{C1})$ can be determined by its payload which, refers to the maximum weight that the drone can carry, which affects the process of delivering medical equipment and supplies, as the UAV has a high payload, and can carry heavy equipment effectively and with low cost. Besides the speed of the UAV in delivering the package. Besides, the distance /criterion refers to the maximum distance that an unmanned aircraft can travel at one time. The physical feature criterion$(\mathrm{C2})$, includes safety, which refers to the protection system used in the UAV to ensure that the package arrives safely, in addition to the control system, which refers to how much manual labor is needed to operate the UAV. The timing criterion,$(\mathrm{C3})$ can determined by clock synchronization to ensure the success of UAV delivery operations, it is crucial to have real-time clock synchronization. This synchronization helps to prevent delays, errors, and other issues by ensuring accurate timing throughout the delivery process. By implementing real-time clock synchronization, UAV delivery companies can ensure smooth and efficient operations. Besides flight time which, refers to the maximum period of time that the UAV can fly in the air.

Table 2. The main criteria and sub-criteria of our model.

Main criteria	Sub-criteria
performance C1	Payload C11
	Speed C12
	Distance C13
Physical feature C2	Control system C21
	Safety C22
Timing C3	Clock synchronization C31
	Flight time C32

Step 3: Four experts start to evaluate the main criteria, as shown in Tables 3, 4, 5, and 6, then the expert's decision matrices will converted into crisp matrices by utilizing Eq. (1), using the scale in Table 1, as shown in Tables 7,8,9 and 10.
Step 4: All the crisp decision matrices must collected into one aggregated matrix by utilizing Eq. (2), as shown in Table 11.
Step 5: After collecting the expert decision matrices into one aggregated matrix, the CRITIC method will be utilized to get the criteria weights, firstly we construct the normalized matrix for the main criteria based on the CRITIC method by utilizing Eq. (3), as shown in Table 12. Table 13 shows, the standard division of each criterion by utilizing Eq. (4). Table 14 shows, the linear correlation coefficient symmetric matrix between each pair of the main criteria. Table 15 shows, the measure of the conflict by utilizing Eq. (5). Table 16 shows, the final weight of the main criteria by calculation of the quantity of the information in relation to each criterion by utilizing Eq. (6) and (7), where the timing ($\mathrm{C3}$) is the highly preferred criterion to other criteria with weight equal to 0.03042516 and final ranking of the main criteria as $\mathrm{C3} > \mathrm{C2} > \mathrm{C1}$, as shown in Figure 2. To calculate the weight of sub-criteria, we will repeat the steps from step three to step five, as we did in the main criteria, thus:
For the performance sub-criteria, after the experts evaluate the performance sub-criteria, we will convert the expert's decision matrices into a crisp matrix by utilizing Eq. (1), these matrices are collected into one aggregated matrix by applying Eq. (2) as shown in Table 17. We apply the CRITIC method on the aggregated matrix to get the performance sub-criteria weight, as shown in Table 18. Figure 3, shows that the payload ($C11$)is the highly preferred performance sub-criteria over the other performance sub-criteria with a weight equal to 0.441945, and the final ranking of the performance sub-criteria as$C11 > C13 > C12$, as shown in Figure 3.
For physical feature sub-criteria, Table 19, shows the aggregated matrix of physical feature sub-criteria by utilizing Eq. (2). Table 20, shows the calculation of the physical feature sub-criteria weight by the CRITIC method. Figure 4, shows that the $\mathrm{C22}$ is the highly preferred physical feature sub-criteria over the other physical feature sub-criteria with a weight equal to 0.501386, and the final ranking of the physical feature sub-criteria as $\mathrm{C22} > \mathrm{C21}$. For timing sub-criteria in level 2, Table 21, shows the aggregated matrix of the timing sub-criteria by utilizing Eq. (2). Table 22 shows the calculation of the timing sub-criteria weight in level 2 by the CRITIC method. As shown in Figure 5, $\mathrm{C31}$ is the highly preferred sub-criteria in level 2 over the other timing sub-criteria with a weight equal to 0.501905. After completing the calculation of the weights of all sub-criteria, we can obtain the final weights for the criteria as shown in Table 23. Figure 6 shows that the $\mathrm{C31}$ is the highly preferred criterion over the other criteria with a weight equal to 0.220895, $\mathrm{C31} > \mathrm{C32} > \mathrm{C22} > \mathrm{C21} > \mathrm{C11} > \mathrm{C13} > \mathrm{C12}$. As shown, the time criterion followed by the safety criterion are the high priority based on the presented scenario.
Step 6: After calculating the weight of the main criteria and sub-criteria, apply the MARICA method to rank the alternatives and choose the best UAV suitable for our scenario. For the main criteria: firstly the aggregated matrix in Table 11 is represented as the decision matrix, then establishes the preferences according to alternatives $\mathrm{p_{Ai}}$ by utilizing Eq. (8), in our scenario $\mathrm{p_{Ai}} = \frac{1}{4} = 0.25$. The theoretical evaluation matrix $\mathrm{T_p}$ is calculated by utilizing Eq. (10) using the weight of the main criteria in Table 16 that were calculated before by the CRITIC method, as shown in Table 24. Table 25 shows the actual theoretical evaluation matrix $\mathrm{T_r}$ by utilizing Eq. (12), note that all the criteria are benefit criteria. Table 26 shows, the total gap matrix by utilizing Eq. (14). Table 27 shows, the final value of criterion functions ($\mathrm{Q_i}$) by alternatives that are calculated by utilizing Eq. (15). According to Figure 7, $\mathrm{A2}$ is the one with the highest rank, whereas, the alternative with the lowest value of the total gap ($\mathrm{Q_i}$), is the best alternative that will be chosen; thus, the alternatives ranked as$\mathrm{A2} > \mathrm{A4} > \mathrm{A3} > \mathrm{A1}$. So, decision-makers will choose the $\mathrm{A2}$ for medical supply delivery in our scenario. For the sub-criteria: apply the same MARICA method steps thus, Table 28 shows, the final value of criterion functions ($\mathrm{Q_i}$) by alternatives that are calculated by utilizing Eq. (15) in the performance sub-criteria,

note that, we using Table 17 as the decision matrix of the performance sub-criteria and using the weight in Table 18 that was calculated before by the CRITIC method. Figure 8 shows that A2 is the one with the highest rank according to the performance sub-criteria, where, A2 is the lowest value of the total gap (Q_i) in performance sub-criteria, thus, the alternatives ranked as $2 > A4 > A3 > A1$. Then, A2 is the best alternative that will be chosen according to performance sub-criteria. Table 29 shows, the final value of criterion functions (Q_i) by alternatives that are calculated by utilizing Eq. (15) in the physical feature sub-criteria using Table 19 as the decision matrix of the physical feature sub-criteria and using the weight in Table 20 that was calculated before by the CRITIC method. Figure 9 shows that, also A2 is the one with the highest rank according to physical feature sub-criteria. Table 30 shows, the final value of criterion functions (Q_i) by alternatives according to timing sub-criteria. Figure 10 shows that, also A2 is the one with the highest rank according to timing sub-criteria. According to the previous results, the best UAV according to the proposed scenario is A2.

Table 3. Decision matrix of Expert1 for the main criteria.

Alternatives	Main Criteria		
	C1	C2	C3
A1	VB	MB	B
A2	VVG	G	VVG
A3	M	MG	G
A4	G	VG	MG

Table 4. Decision matrix of Expert2 for the main criteria.

Alternatives	Main Criteria		
	C1	C2	C3
A1	MB	B	VB
A2	EG	VG	VVG
A3	MG	G	M
A4	VG	G	MG

Table 5. Decision matrix of Expert3 for the main criteria.

Alternatives	Main Criteria		
	C1	C2	C3
A1	B	VB	MB
A2	G	VVG	VG
A3	G	M	G
A4	VG	MG	VG

Table 6. Decision matrix of Expert4 for the main criteria.

Alternatives	Main Criteria		
	C1	C2	C3
A1	MB	MB	VB
A2	EG	VG	VVG
A3	M	G	MG
A4	MG	VG	G

Table 7. Crisp decision matrix of Expert1 for the main criteria.

Alternatives	Main Criteria in Level 1		
	C1	C2	C3
A1	0.1833333	0.3833333	0.2833333
A2	0.9	0.716667	0.9
A3	0.5	0.616667	0.716667
A4	0.716667	0.816667	0.616667

Table 8. Crisp decision matrix of Expert2 for the main criteria.

Alternatives	Main Criteria in Level 1		
	C1	C2	C3
A1	0.3833333	0.2833333	0.616667
A2	1	0.816667	0.9
A3	0.616667	0.716667	0.5
A4	0.816667	0.716667	0.616667

Table 9. Crisp decision matrix of Expert3 for the main criteria.

Alternatives	Main Criteria in Level 1		
	C1	C2	C3
A1	0.2833333	0.61666667	0.383333333
A2	0.716667	0.9	0.81666667
A3	0.716667	0.5	0.71666667
A4	0.816667	0.61666667	0.81666667

Table 10. Crisp decision matrix of Expert4 for the main criteria.

Alternatives	Main Criteria in Level 1		
	C1	C2	C3
A1	0.3833333	0.3833333	0.616667
A2	1	0.816667	0.9
A3	0.5	0.716667	0.616667
A4	0.616667	0.816667	0.716667

Table 11. Aggregated matrix for the main criteria.

Alternatives	Main Criteria		
	C1	C2	C3
A1	0.30833333	0.41666667	0.475
A2	0.90416667	0.8125	0.879167
A3	0.58333333	0.6375	0.6375
A4	0.74166667	0.74166667	0.691667

Table 12. Normalized matrix for main criteria.

Alternatives	Main Criteria		
	C1	C2	C3
A1	0	0	0
A2	1	1	1
A3	0.46153846	0.55789473	0.402061524
A4	0.72727273	0.82105264	0.536082857

Table 13. The standard division of each main criterion.

Alternatives	Main Criteria		
	$C1$	$C2$	$C3$
$\boldsymbol{A1}$	0	0	0
$\boldsymbol{A2}$	1	1	1
$\boldsymbol{A3}$	0.46153846	0.55789473	0.402061524
$\boldsymbol{A4}$	0.72727273	0.82105264	0.536082857
$\sigma_j = \sqrt{\frac{(\sum_{i=1}^{m} x_{ij} - \bar{x_j})^2}{m-1}}$	0.42591852	0.43609109	0.412285252

Table 14. The linear correlation coefficient symmetric matrix.

	Main Criteria		
	C1	C2	C3
C1	1	0.9921657	0.97738703
C2	0.9921657	1	0.94881659
C3	0.97738703	0.94881659	1

Table 15. The measure of the conflict.

	Main Criteria			**Con** $= \sum_{k=1}^{m}(1 - r_{jk})$
	C1	C2	C3	
C1	0	0.0078343	0.02261297	0.0304473
C2	0.0078343	0	0.05118341	0.0590177
C3	0.02261297	0.05118341	0	0.0737964

Table 16. The weight of the main criteria.

Main criteria	$\sigma_j = \sqrt{\frac{(\sum_{i=1}^{m} x_{ij} - x_j^-)^\wedge 2}{m-1}}$	**Con** $= \sum_{k=1}^{m}(1 - r_{jk})$	$C_j = \sigma_j * \sum_{k=1}^{m}(1 - r_{jk})$	$w_j = \frac{C_j}{\sum_{k=1}^{m} C_j}$	**Percentage weight**
C1	0.4259185	0.03044726	0.01296805	0.18758855	18.70%
C2	0.4360911	0.0590177	0.02573709	0.372298287	37.20%
C3	0.4122853	0.07379637	0.03042516	0.440113164	44.00%

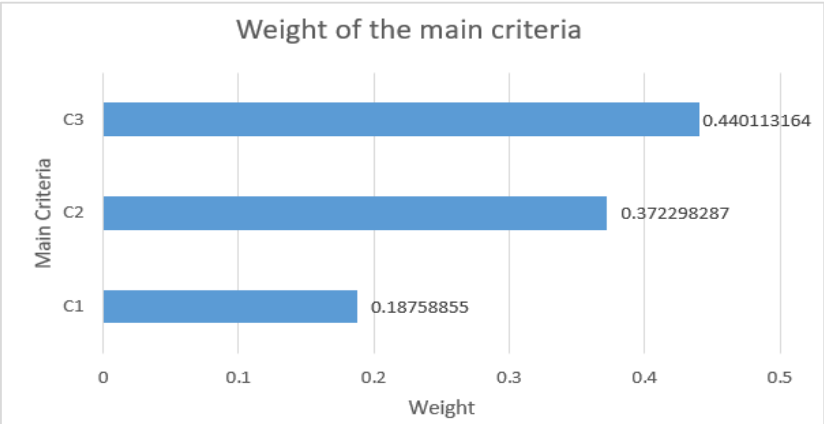

Figure 2. The weight of the main criteria by the CRITIC method.

Table 17. Aggregated matrix for the performance sub-criteria.

Alternatives	**Performance Sub-criteria**		
	C11	C12	C13
A1	0.14166667	0.25833333	0.20833333
A2	0.7875	0.95	0.74166667
A3	0.44583333	0.52916667	0.3875
A4	0.64166667	0.76666667	0.58333333

Table 18. The weight of the performance sub-criteria.

Performance Sub-criteria	$\sigma_j = \sqrt{\frac{(\sum_{i=1}^{m} x_{ij} - x_j^-)^2}{m-1}}$	$\text{Con} = \sum_{k=1}^{m}(1 - r_{jk})$	$C_j = \sigma_j * \sum_{k=1}^{m}(1 - r_{jk})$	$w_j = \frac{C_j}{\sum_{k=1}^{m} C_j}$	Percentage weight
C11	0.4324346	0.01504891	0.006508	0.441945	44.10%
C12	0.4331873	0.0057793	0.002504	0.170018	17.00%
C13	0.4350459	0.01313395	0.005714	0.388037	38.80%

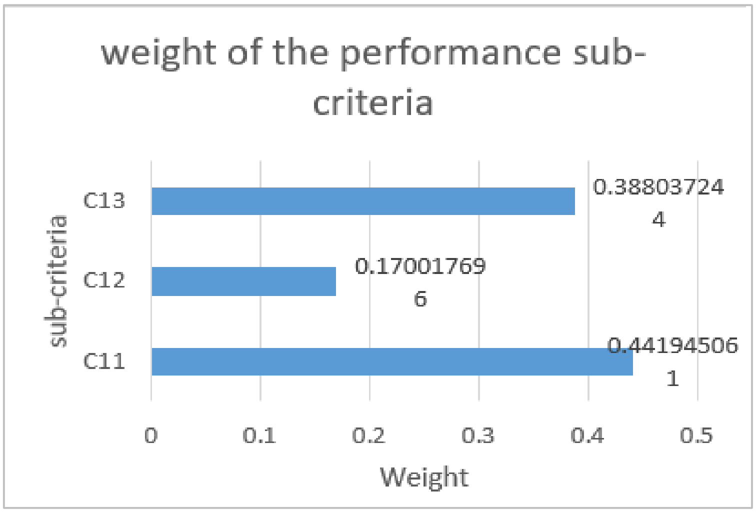

Figure 3. The weight of the performance sub-criteria by the CRITIC method.

Table 19. Aggregated matrix for the physical feature sub-criteria.

Alternatives	The physical Feature Sub-criteria	
	C21	C22
A1	0.2583333	0.14583333
A2	0.9041667	0.8125
A3	0.6916667	0.58333333
A4	0.7916667	0.70833333

Table 20. The weight of the physical feature sub-criteria.

Physical feature Sub-criteria	$\sigma_j = \sqrt{\frac{(\sum_{i=1}^{m} x_{ij} - x_j^-)^2}{m-1}}$	$\text{Con} = \sum_{k=1}^{m}(1 - r_{jk})$	$C_j = \sigma_j * \sum_{k=1}^{m}(1 - r_{jk})$	$w_j = \frac{C_j}{\sum_{k=1}^{m} C_j}$	Percentage weight
C21	0.437296	0.0004492	0.000196	0.498614	49.80%
C22	0.439726	0.0004492	0.000198	0.501386	50.10%

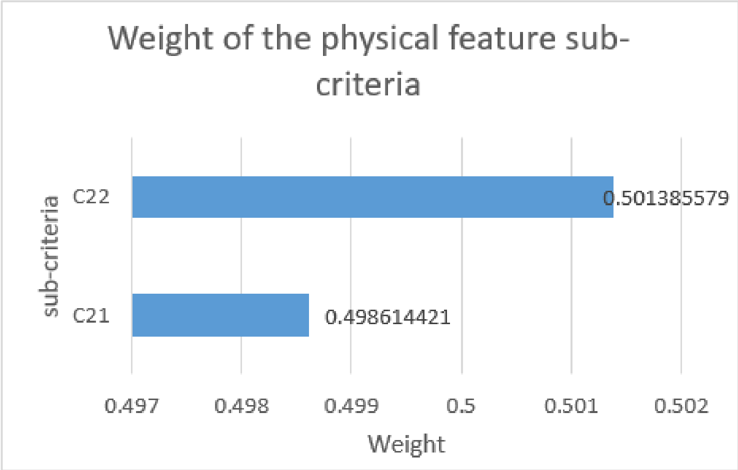

Figure 4. The weight of the physical feature sub-criteria by CRITIC method.

Table 21. Aggregated matrix for the timing sub-criteria.

Alternatives	**The Timing Sub-criteria**	
	C31	C32
A1	0.3	0.2625
A2	0.95	0.88333333
A3	0.58333333	0.58333333
A4	0.71666667	0.6625

Table 22. The weight of timing sub-criteria.

Physical feature Sub-criteria in Level 2	$\sigma_j = \sqrt{\frac{(\sum_{i=1}^{m} x_{ij} - x_j^{-})^2}{m-1}}$	**Con** $= \sum_{k=1}^{m}(1 - r_{jk})$	$C_j = \sigma_j * \sum_{k=1}^{m}(1 - r_{jk})$	$w_j = \frac{C_j}{\sum_{k=1}^{m} C_j}$	**Percentage weight**
C31	0.41734	0.004582	0.001912	0.501905	50.19%
C32	0.414172	0.004582	0.001898	0.498095	49.80%

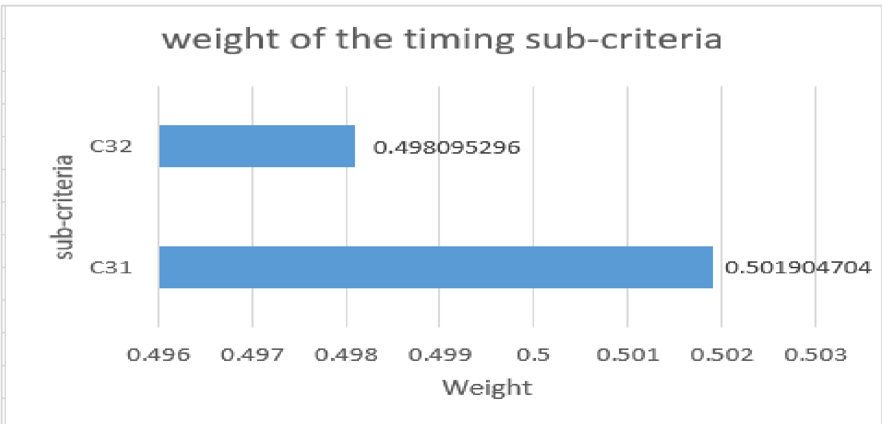

Figure 5. The weight of the timing sub-criteria by CRITIC method.

Table 23. The Final weight of the criteria.

Criteria	The Final weight
C11	0.082904
C12	0.031893
C13	0.072791
C21	0.185633
C22	0.186665
C31	0.220895
C32	0.219218

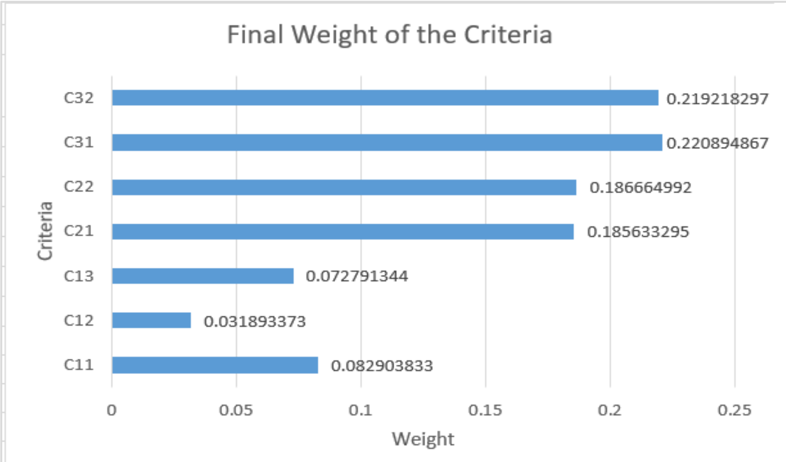

Figure 6. The rank of the final weight of the criteria.

Table 24. The theoretical evaluation matrix in the main criteria

		Main Criteria		
Weights		0.18758855	0.372298287	0.440113164
PA	0.25	C1	C2	C3
$\mathbf{T_p}$		0.04689714	0.093074572	0.110028291

Table 25. The actual theoretical evaluation matrix T_r in the main criteria.

	Main Criteria		
Weights	0.18758855	0.372298287	0.440113164
Alternatives	C1	C2	C3
A1	0	0	0
A2	0.046897138	0.093074572	0.110028291
A3	0.021644832	0.051925813	0.044238142
A4	0.034107009	0.076419123	0.058984281

Table 26. The total gap matrix G in the main criteria.

	Main Criteria		
Weights	0.18758855	0.372298287	0.440113164
Alternatives	C1	C2	C3
A1	0.046897138	0.093074572	0.110028291
A2	0	0	0
A3	0.025252305	0.041148758	0.065790149
A4	0.012790128	0.016655449	0.05104401

Table 27. The final value of criterion functions (Q_i) according to the main criteria.

Alternatives	Qi
A1	0.25
A2	0
A3	0.132191212
A4	0.080489588

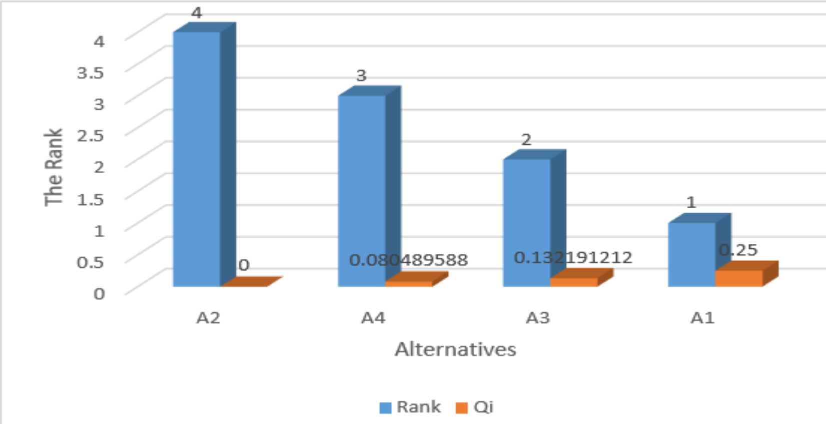

Figure 7. The Rank of alternatives according to the main criteria.

Table 28. The final value of criterion functions (Q_i) according to the performance sub-criteria

Alternatives	Qi
A1	0.25
A2	0
A3	0.148732
A4	0.042832

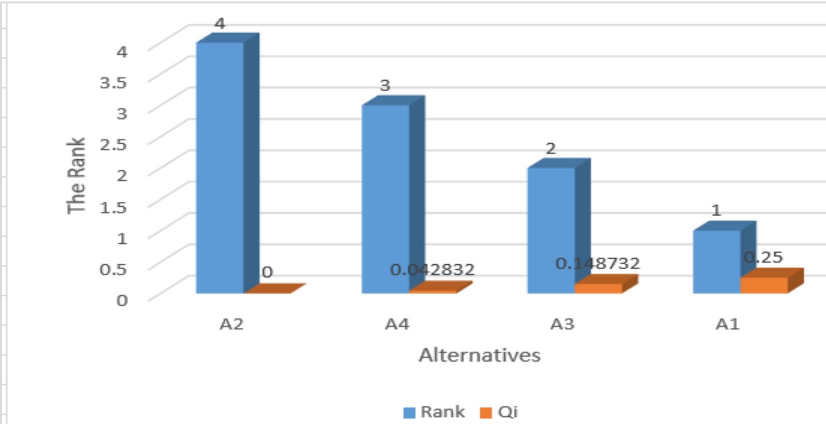

Figure 8. The Rank of alternatives according to the performance sub-criteria.

Table 29. The final value of criterion functions (Q_i) according to the physical feature sub-criteria

Alternatives	Qi
A1	0.25
A2	0
A3	0.084102878
A4	0.041299224

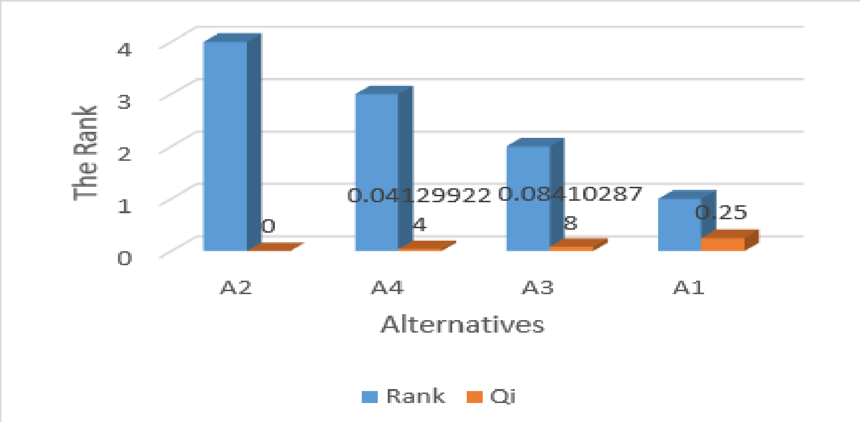

Figure 9. The Rank of alternatives according to the physical feature sub-criteria.

Table 30. The final value of criterion functions (Q_i) according to the timing sub-criteria

Alternatives	**Qi**
A1	0.25
A2	0
A3	0.130954026
A4	0.089336438

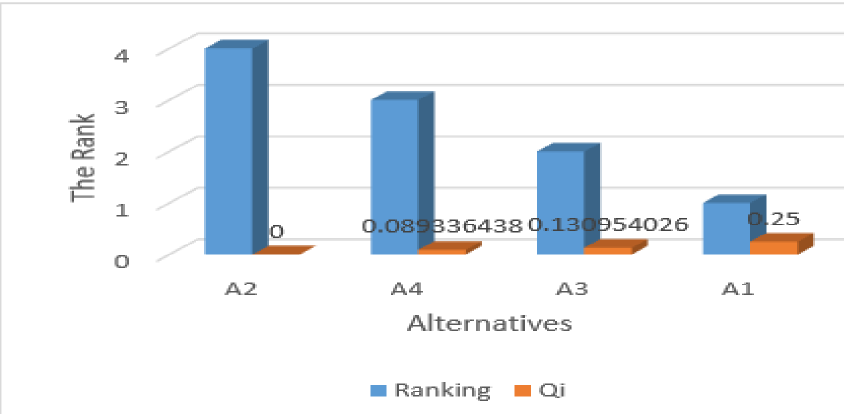

Figure 10. The Rank of alternatives according to the timing sub-criteria.

4. Managerial implications

Since the selection process is a complex and hard mission due to numerous and conflicting criteria that exist nowadays, so we need an efficient and effective MCDM technique. Therefore, in this research, we present a neutrosophic model to evaluate UAVs and choose the best among the alternatives, which are used in the operations of delivering and supplying medical supplies. The presented model can be a dominant guide for firms, organizations, and governments to make precise decisions about any medical, social, economic, and environmental problems.

5. Conclusion and Future Work

A new MCDM model was proposed to evaluate UAVs and choose the appropriate one among the set of UAVs for the process of delivering medical supplies to improve health care and contribute to saving patients. The experiment study results demonstrated that the proposed model is capable of dealing with ambiguity in decision problems effectively. In addition, it takes into account the inter-correlation between the criteria, whether positive or negative, and determines the priority of the criteria and weighting them effectively by applying the CRITICA method. Also, using the MARICA Method, allows for effective evaluation of alternatives, as it provides a symmetric framework and does not require complex mathematical calculations. According to our experimental study, the time and safety factors are the two criteria that are most preferred over the other criteria, and based on them, the best UAV was chosen by applying our model.

In our future work, we will use the CRITIRIA method along with another approach to evaluate alternatives and make comparisons between them.

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Author Contributions
All authors contributed equally to this research.

Data availability
The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

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Conflict of interest
The authors declare that there is no conflict of interest in the research.

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