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ORIGINAL ARTICLE

Two-phase multi-expert knowledge approach by using fuzzy clustering and rule-based system for technology evaluation of unmanned aerial vehicles

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Abstract
Unmanned aerial vehicles (UAVs) are utilized in many different areas for different aims such as the benefit of humanity, safety control, traffic control, crop monitoring, scientific research, and commercial applications. Moreover, the UAVs are also successfully utilized for military operations, such as surveillance of an area and counter-terrorism actions. Evaluating them through the technological perspective is quite significant and should be considered from multiple perspectives. In this context, it will be more beneficial to construct a methodology for an efficient evaluation process. The fuzzy set theory (FST) can also be integrated into this methodology to improve its sensitiveness and flexibility. In this paper, a novel methodology integrating fuzzy *c*-means (FCM) clustering and fuzzy inference system (FIS) has been suggested for the technical evaluation of UAVs. While the FCM clustering algorithm has been utilized to determine the clusters, rules have been created for the FIS through expert assessments, and alternative UAV technologies have been prioritized. For the evaluation procedure, the hierarchical structure of the technology evaluation features has been determined by fusing expert knowledge, literature review, and related ISO standards. Through the FCM clustering algorithm, alternative vehicles have been clustered based on the sub-features of each main feature. Then, FIS has been conducted by using experts' knowledge from the fields of military technologies in UAVs and armed UAVs to obtain the technology indices of the eight UAVs locally produced and used in Turkey. The results demonstrate that the proposed methodology can be successfully applied by the managers or research and development (R&D) engineers for evaluation of the UAV technologies to consider cardinal and linguistic data. Additionally, a comparative analysis based on self-organizing map (SOM) and fuzzy *k*-means algorithms has also been applied for the proposed method, and their performances have been compared.

Keywords Unmanned aerial vehicles · Decision making · Fuzzy sets · Fuzzy c-means clustering · Fuzzy inference system · Technology evaluation

1 Introduction

Unmanned aerial vehicles (UAVs), also known as drones, which are aircraft operating without human pilots, have become popular in civilian and military fields because of their versatility and flexibility. They are utilized for different applications such as traffic monitoring, tracking and surveillance, remote sensing, crop monitoring, military operations, and search and rescue activities. The UAVs are operated with embedded sensors, cameras, and communication equipment and can be used for situations where human intervention is risky, dangerous, impossible, or expensive [1]. On the other hand, it is necessary to consider some technical and non-technical challenges related to the

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usage of UAV technology. While technical challenges include cyber-attacks, virus contamination, communication disruptions, and vehicle crashes, legislative and regulatory obligations, security violations, privacy invasions, and misuse by individuals can be ensampled as non-technical concerns [2]. These issues are confronted in critical missions of the UAV and may prevent them from providing several advantages such as detection, tracking, better inspection ability, and more extensive coverage area.

Despite their challenges, UAVs have become used in many different areas of life due to essential developments in their technology, which can be distinguished between three categories: safety control, scientific research, and commercial applications [3]. It has a wide range of applications in several areas, including firefighting and traffic monitoring, search and rescue operations, monitoring, forecasting, situational awareness in disaster management, meteorological observation, precision agriculture or pesticide spraying in agriculture, and delivery of goods in logistics [4–8]. In addition to its usage for these commercial applications and scientific researches, one of the most highlighted areas is the military, which is used for wide-area surveillance, close-in reconnaissance, early warning detection, localization, and saturation strike.

Due to the common usage of UAVs for military operations, it will be essential to introduce an efficient methodology to evaluate UAV alternatives in terms of technological aspects to be aware of the available UAVs capacities and restrictions. To create a comprehensive perspective involving international standards, mentioned features in the literature, and expert knowledge will promise meaningful outcomes for the decision-makers. This is also important for the transition of manned aircraft to unmanned aircraft since UAV technologies have less cost and lower risk for humans in case of an accident [6]. Moreover, evaluating the technology level of the UAVs is crucially important within the competence and effectiveness context based on a wide range of criteria to obtain. Therefore, a comprehensive evaluation procedure promises useful outcomes for the managers to determine the most appropriate UAV during their selection process for military purposes.

Based on the findings of a detailed investigation presented in Sect. 2, a novel methodology consists of fuzzy *c*-means (FCM) clustering and fuzzy inference system (FIS) for technology evaluation, and prioritization of military UAV alternatives has been proposed in this paper. In the proposed methodology, experts' knowledge and experience expressed as linguistic variables are used in the FCM phase with cardinal data (inputs of standard qualifications of the UAVs such as length, altitude) to create a comprehensive decision-making structure. Integrating these two techniques in a decision-making methodology promises meaningful outputs for the applications since the output of the clustering algorithms is suitable for the rule-based systems. This methodology will be useful for the comprehensive assessment of military UAV alternatives in terms of critical features for both operational and strategic levels. Moreover, the proposed methodology offers an efficient analytical tool for researchers and managers to evaluate critical and up-to-date UAV technologies. In this context, this paper has performed a prioritization study for eight UAVs that are locally produced and used in Turkey. The FCM clustering method has been used to determine the prioritized clusters with the experts' evaluations. Through experts' evaluations, rules have also been created for the FIS, and all alternative UAV technologies have been prioritized. Additionally, a comparative analysis has been adopted to compare performance and obtain the results of the suggested methodology. For this aim, two methods, self-organizing map (SOM) and fuzzy *k*-means algorithms, have been applied. Based on the obtained results, findings and possible managerial implications are discussed.

The rest of this paper has been organized as follows: In Sect. 2, a literature analysis related to existing UAV applications has been summarized and it has been aimed to indicate the writing motivation and novelty of this paper. In Sect. 3, the proposed methodology consists of FCM clustering, and FIS methods have been introduced. In Sect. 4, an application for technology evaluation and prioritization of military UAV alternatives using the proposed methodology has been realized. Besides, comparative analyses, simulations for discussions, and managerial implications realized to check the robustness of the proposed methodology have been presented. The paper has been concluded with obtained results and future research suggestions into Sect. 5.

2 A literature analysis

In this study, it is aimed to propose a novel fuzzy-based decision-making methodology integrating FCM clustering and FIS methods for technology evaluation and prioritization of UAV alternatives. For this aim, the application areas of UAVs both in civil and military manner and desired to present an efficient approach for the evaluation of UAV technologies due to their importance in practical applications have been analyzed. At this point, it is necessary to examine UAV-related studies in the literature and to reveal the novelty of both our methodology and our decision-making problem according to existing papers realized with respect to UAV technologies. Therefore, a comprehensive literature analysis has been conducted related to UAVs.

Based on the literature review, UAV-based applications have been carried out by using five main approaches, fuzzy inference system (FIS), artificial neural networks (ANNs), fuzzy clustering algorithms (FCAs), multi-criteria decision making (MCDM) methods, and heuristic optimization methods (HOMs). During the analysis of the gathered studies, it is aimed to clarify which of the techniques can be efficient for our case and what are the possible evaluation criteria for the technology evaluation of the UAVs. Moreover, since the application environment involves both cardinal and linguistic data, it is also important that the mentioned techniques have the ability to involve uncertainty during mathematical calculations. Through that, Table 1 is constructed for the analysis of the five main approaches based on their input data and consideration of uncertainty.

For the methodology part, as a result of this detailed literature analysis based on the technology evaluation of UAVs and the proposed methodology, qualitative data obtained from the experts was not involved in the meta-heuristics studies. Moreover, pairwise comparison techniques such as AHP are not suitable for cases with interdependency between the sub-features within the MCDM methods. For distance-based MCDM methods such as TOPSIS, VIKOR, EDAS, CODAS, it has been observed that deviation in one indicator in the ideal solution powerfully affects the results. For the FISs, the most essential phase of the application is constructing a rule-based system and feeding the system with meaningful inputs. Based on the mentioned papers from the literature, it is observed that the inputs are mostly determined without a verified algorithm. Therefore, it is essential to feed the rule-based system with inputs gathered from the algorithms proven their high efficiency.

Another analysis is carried out for the determination of the decision-making structure of the application. UAV technologies can be classified based on several features such as weight, altitude and range, wing and rotor, and application area. On the other hand, a classification can be made according to their field of use, which can be categorized as agricultural usage, civilian usage, and military usage. From a general perspective, there are many disadvantages and threats to the usage of UAVs for different applications. These challenges can be ensampled as regulations and legislation, training and test facilities, social acceptance, battery technologies, sensor accuracy, and security threats and authentication [2].

Table 1 Analyzed studies with respect to applied techniques and data type

Paper ID	FIS	ANN	FCA	MCDM	HOM	Cardinal data	Linguistic data	Considering uncertainty
[9]	✔	✔				✔		✔
[10]			✔			✔		✔
[11]				✔			✔	✔
[12]			✔			✔		✔
[13]		✔				✔		
[14]	✔				✔	✔	✔	✔
[15]			✔			✔		✔
[16]	✔	✔				✔	✔	✔
[17]			✔		✔	✔		✔
[18]				v		✔		
[19]	✔						✔	✔
[20]					✔	✔		
[21]			✔			✔		✔
[22]	✔	✔				✔	✔	✔
[23]			✔			✔		✔
[24]				✔			✔	✔
[25]			✔			✔		✔
[26]	✔	✔				✔	✔	✔
[27]		✔				✔		
[28]					✔	✔		
[29]				✔		✔	✔	✔
[30]	✔					✔	✔	✔

While agricultural use includes different applications such as crop monitoring, irrigation, spraying, and field soil analysis, examples of civil use applications include photography, disaster management, search and rescue operations, geographic mapping, and weather forecasting. Furthermore, military usage involves different applications such as military surveillance, military security, and bomb recognition [31]. Based on the scope of this study, military armed drones (UAVs) have been evaluated based on the technological abilities and disabilities with a constructed context. Through that, inspection and mapping/surveying (delivery can also be considered part of counterstrike attacks in the military context if the vehicle aims to drop a bomb to a determined location or drop requirements to the allies) are considered. The most highlighted limits of the military UAVs in management are energy consumption, source of energy, the need for large bandwidth communications, vulnerability to jamming, and low survivability in military operations. Considering these aspects in a decision-making procedure involving both cardinal and linguistic data can result in promising outputs for both managers and researchers in this field. Based on the comprehensive review, these issues are considered by involving the communication, availability of energy supply systems, software dependability, hardware dependability, contingency management sub-features for the evaluation process.

Through the analysis, evaluation criteria, which are given in Table 2, are determined. Therefore, for the application part, it has been observed that UAV applications are mainly the studies based on controlling, energy consumption, and cybersecurity. Besides, no analysis involving both cardinal and linguistic data has been encountered for the technology evaluation with respect to a military context. Unlike these studies, a comprehensive evaluation framework of the military UAV technologies by considering both international standards for UAVs, studies related to the UAVs, and expert knowledge has been introduced using qualitative and quantitative data. Considering both types of data in an integrated methodology enables results not only based on standard qualifications such as wingspan, length, payload capacity, speed, or altitude but also human perceptions and perspectives. This flexibility also allows us to build such a comprehensive context to evaluate the UAVs. Through that, human perceptions and perspectives are handled using the computing with words concept, which enables to involve human evaluations as inputs of the mathematical operations effectively. For the results, a fuzzy inference system has been applied to obtain the technology indices of the UAVs, since rule-based systems are one of the most efficient methods to consider qualitative data.

In light of this analysis, the current study aims to bridge the mentioned research gap using the following objectives: (1) What are the essential criteria and sub-criteria playing a role towards the technology evaluation of the UAV alternatives? (2) How could involve both quantitative and qualitative data in a decision-making procedure considering the knowledge and expert-based evaluations? (3) What are the possible managerial implications based on the comparisons and discussions for the carried applications?

Therefore, in this paper, differently from conventional prioritization and ranking methods, based on the constructed context, an integrated methodology consists of fuzzy *c*-means clustering approach, and a fuzzy inference system has been proposed. The proposed methodology has also been compared with the neural network approach, self-organizing map (SOM), and clustering method, fuzzy *k*-means clustering to check and discuss its advantages. Moreover, the implications of the results and the methodology dynamics have been presented and discussed.

3 The proposed methodology

In this section, the fuzzy clustering concept, FCM clustering algorithm, FIS, and the proposed methodology utilized for technology evaluation and prioritization of UAV alternatives have been introduced.

3.1 Fuzzy clustering

Before presenting the preliminaries of fuzzy clustering, a broad explanation for the field of machine learning and its components will be useful. Since the machine learning techniques aim to improve the accuracy of the constructed model by using the eligible data set, many algorithms are introduced in the literature to do so. The performed algorithms are applied in many fields such as medical diagnosis, security applications, forecasting of the energy requirements, and pathing. Based on the data set and the aim of the decision-makers, the topic is divided into three main areas, supervised, unsupervised, and reinforcement learning [32]. Unsupervised learning aims to distinguish a set of targets into structural groups, which can be classes or clusters, to identify their memberships with the determined criteria [33]. By contrast with supervised learning or reinforcement learning, there are no explicit target outputs or environmental evaluations associated with each input [34]. Since one of the most important phases of unsupervised learning algorithms is to determine the number of groups and their belongings, clustering techniques are remarkable to apply.

In today's world, a large amount of information has been processed for the decision-making procedure of humans based on their interaction level among themselves and the environment. Through these procedures,

Table 2 Hierarchical structure of evaluation features for the UAV technologies

Safety measures	Cognitive functionality	Endurance to environmental conditions	Standard qualifications	National-level importance
Availability of high risk rated components [64]	Fault detection and vehicle health management [51, 52]	Variation of mission performance with respect to altitude (wind, temperature, humidity, precipitation) [64]	Wingspan [57–59]	Software dependability [55]
Acceptable level of risks to allow planned UAS operations [64]	Situation awareness [51]	The effects of clouds for visual observation [64]	Length [57–59]	Hardware dependability
Availability of obstructions for a UAS operation [64]	Communication [51, 60]	Variation of battery/fuel performance with respect to altitude (wind, icing, humidity, precipitation) [64]	Payload capacity [57]	Availability of energy supply systems [8]
Availability of safety management system [51]	Payload management [51, 60]	Ability to identify turbulence [64]	Endurance [57–59, 61]	International reputation
Effectiveness of risk control systems [51]	Guidance, navigation and control [8, 51, 62]	Durability limits in case of air hazards [64]	Cruise speed [51, 57–61, 63]	
	Failure anticipation and reaction [51]		Operational altitude [57]	
	Flight planning and decision making [51]		Range [57–59]	
	Information/network management [51, 52, 54]			
	Contingency management [51]			
	Target coverage and detection performance [54]			

classification plays a crucial role in making a decision, which can be one of the most primitive activities of human beings [35]. By doing it, humans mostly use their memories to classify the encountered problem/event by seeking its features [36]. Similarly, clustering algorithms search for the most appropriate clusters by separating a finite unlabeled data set into finite and discrete structures [37]. The most prominent problem of clustering is to assign a target into an exact set by using many features, since the target may also have some characteristics of the other set or sets.

Moreover, since the number of conflicting features increases, the decision-making procedure becomes extremely complex, and the boundaries between distinct clusters cannot be sharply defined [38]. Besides, this technique often does not reflect the description of real data, where boundaries between subgroups might be fuzzy [39]. Through that, fuzzy clustering algorithms (FCAs) have been introduced to the literature to increase the ability to reflect the data of the traditional clustering algorithms.

Fuzzy logic is introduced by Zadeh, which is one of the most efficient ways of representing uncertainty by assigning a membership to an element for a set to represent its belonging [40]. In traditional set theory, an element can belong to a set or not; in optimization, a solution is either feasible or not; and in conventional Boolean logic, a statement can be true or false but nothing in between [41]. However, the states and the actions are mostly not precise and cannot be defined in a deterministic environment with a single crisp number in real-life conditions [42]. Therefore, utilizing fuzzy logic in clustering algorithms can be an efficient way to represent uncertainty while obtaining meaningful outputs.

3.2 Fuzzy c-means clustering

FCM clustering is proposed for systems where objects can belong to more than one cluster. A membership function is utilized for each of the objects to indicate their degree of belongings to the determined clusters [43]. The mathematical modeling of the algorithm is presented as follows [43]:

Partitioned set of input data points: $X = \{x_1, x_2, \ldots, x_n\}$.

$$\text{Clusters}: \; C = \{C_1, C_2, \ldots, C_k\}$$

where k is the number of pre-defined clusters and n is the number of samples.

Objective function, to minimize the distance between the samples and the determined clusters, is presented in Eq. (1) as follows:

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{k} \mu_{ji}^m D(x_i \mu_j) \tag{1}$$

where m, greater than 1, is the fuzzy index (for the application, m is set to 2), x_i is the ith data point, D is the Euclidian distance function, and μ_{ji}^m is the membership degree of x_i for the cluster j.

Subject to

$$\sum_{i=1}^{c} \mu_{ij} = 1, 1 \le j \le n \tag{2}$$

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{k} \mu_{ji}^m D(x_i, \mu_j) \tag{3}$$

By using the Lagrange multiplier method, the objective function is updated as in Eq. (4) as follows:

$$J = \sum_{i=1}^{n} \sum_{j=1}^{k} \mu_{ji}^m D(x_i, \mu_j) + \sum_{j=1}^{k} \lambda_k \left(\sum_{i=1}^{n} \mu_{ji} - 1 \right) \tag{4}$$

where $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_n]^T$ is the Lagrange multiplier.

Through that, Eqs. (2–3) are updated as follows:

$$\mu_{ik} = 1 / \sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(m-1)} \quad 1 \le i \le n, 1 \le k \le c \tag{5}$$

where d_{ik} is the distance between the cluster k and element i, d_{jk} is the distance between the cluster k and element j.

$$c_j = \frac{\sum_{k=1}^{n} x_k (\mu_{ik})^m}{\sum_{k=1}^{n} (\mu_{ik})^m}, \quad 1 \le k \le c \tag{6}$$

where c_j is the jth cluster center.

The steps of the FCM clustering are presented in Algorithm 1 as follows:

The process continues until the determined convergence condition is satisfied.

3.3 Fuzzy inference system

FISs are the expert knowledge systems based on *if–then* rules, in which premises and conclusions are expressed employing linguistic terms [44]. Zadeh introduced computing with words (CWWs), a methodology used for uncertain environments containing human-knowledge data defined with linguistic variables [45]. By using the inputs in the form of linguistic variables, FISs enable the process of the data by employing the degree of membership functions.

There are two types of FISs that use different procedures to compute the output data: Mamdani's FIS and Takagi–Sugeno's FIS [46, 47]. Both methods are useful to fulfill the aimed objectives during the decision-making processes, such as classification of the samples, diagnoses, process controls, ranking the alternative solutions [48]. For evaluating the UAV technologies, Mamdani's FIS has been utilized to apply the integrated methodology. The steps of Mamdani's FIS are presented as in Algorithm 2:

Algorithm 1: Fuzzy c-means clustering

Inputs: Evaluations of the samples based on the features(x_{ij}), number of pre-defined clusters(k), fuzziness parameter(m),

Outputs: Clusters($c = \{1,2,\ldots,k\}$), membership degree of the samples to the clusters (μ_{ik})

Begin

Step 1: Evaluate the samples based on the features

Step 2: Determine the number of clusters

Step 3: Determine fuzziness parameter

Step 4: **While** $\|U^{(k+1)} - U^{(k)}\| < \varepsilon$ **do**

Calculate the centers of the clusters

Step 5: **Update** $U^{(k)}, U^{(k+1)}$

End

End

Algorithm 2: Rule-based process for calculation technology index value

Inputs: Clusters($c = \{1,2,\ldots,k\}$), membership degree of the samples to the clusters (μ_{ik})
Outputs: Technology indices of the vehicles (TI_i)
Begin

Step 1: Construct a rule-based system (see Table 7) using experts' knowledge from military technologies in UAVs and armed UAVs.

for $i = 1 : n$ **do**

Step 2: Use the membership degree of the inputs, which are determined in FCM as the inputs of FIS. To achieve this, take the minimum of membership degree of Safety Measures (s), Cognitive Functionality (c), Endurance to Environmental Conditions (e), Standard Qualifications (q), National-level Importance (n) to find T_{sceqn} by using Eq. (7).

$$T_{sceqn} = min(\mu_s, \mu_c, \mu_e, \mu_q, \mu_n) \tag{7}$$

Step 3: Determine the class of each vehicle as one of the following values: VL: Very Low, L: Low, M: Medium, H: High, VH: Very High by using Table 7.

Step 4: Take the maximum of T_{sceqn} values that belong to the same class to determine VL, L, M, H, and VH values by using Eqs. (8)-(12) for defuzzification procedure.

$$VL = \max(T_{sceqn})\ \forall\ T_{sceqn} \in \mathbf{VL} \tag{8}$$

$$L = \max(T_{sceqn})\ \forall\ T_{sceqn} \in \mathbf{L} \tag{9}$$

$$M = \max(T_{sceqn})\ \forall\ T_{sceqn} \in \mathbf{M} \tag{10}$$

$$H = \max(T_{sceqn})\ \forall\ T_{sceqn} \in \mathbf{H} \tag{11}$$

$$VH = \max(T_{sceqn})\ \forall\ T_{sceqn} \in \mathbf{VH} \tag{12}$$

Step 5: Defuzzify VL, L, M, H, and VH values by using Eq. (13) to obtain technology indices (TI_i) of the vehicles [49].

$$TI_i = \frac{1\times VL+3\times L+5\times M+7\times H+10\times VH}{VL+L+M+H+VH} \tag{13}$$

End

End

3.4 The proposed integrated fuzzy-based methodology

The proposed methodology is an integrated approach consisting of FCM clustering and FIS. For the first phase of the proposed methodology, a hierarchical structure of the technology evaluation features is determined by combining expert knowledge, literature review, and ISO standards. There are two levels in the hierarchical structure. In the first level, there are main features of the UAVs, which are the input parameters of the FIS. There are sub-factors related to the corresponded main features in the second level, which are the evaluation criteria of the alternatives. For the second phase, a consensus of the experts evaluates the UAVs with respect to evaluation criteria to construct the dataset of the FCM clustering. For the third phase, Algorithm 1 is run concerning each main criterion to determine the clusters. Based on the clusters, each of the UAVs is clustered, and the corresponded membership degree is assigned. Therefore, for each of the UAV alternatives, there are different clusters and memberships for each of the first level features as outputs. By the way, clusters are put in order from most desired one to least by considering current situations of the most efficient technologies of the UAVs. For the next phase, these outputs are used as inputs of the FIS. The FIS procedure is carried out using experts' knowledge from military technologies in UAVs and armed UAVs. The rules are constructed through their evaluations. After the FIS procedure presented in Algorithm 2 is run for each of the evaluated alternatives, the prioritization of the UAV technologies is completed, and the most appropriate UAV system is determined. The flowchart of the proposed methodology is given in Fig. 1 for a visual representation and to summarize the decision-making system.

4 An application for technology evaluation of the UAVs

In this section, the proposed methodology has been applied for technology evaluation and prioritization of the unmanned aerial vehicles (UAVs) that are utilized for military operations. Since UAVs have great potential in the defense industry for both defensive and attack aims, several vehicles are introduced to the market. Eight of them have been selected, and five main features have been determined, which are F1-Safety Measures [8, 52, 64], F2-Cognitive Functionality [51, 53–59], F3-Endurance to Environmental Conditions [50, 55], F4-Standard Qualifications, F5-National-level Importance for the evaluation. Moreover, when the characteristics of UAVs are examined, the determined sub-features can be considered for the evaluation of the UAV technologies presented in Table 2.

Among them, F4-Standard Qualifications consist of six sub-features, and the value of them can be obtained via company reports as in Table 3.

A consensus-based decision-making procedure has been conducted for the evaluations through this structure. Since evaluating the sub-factors of the F1-Safety Measures, F2-Cognitive Functionality, F3-Endurance to Environmental Conditions, and F5-National-level Importance are subjective, computing with words concept has been considered. Based on that, the linguistic scales presented in Table 4 have been constructed for the evaluation process of the consensus.

After gathering input data for the FCM clustering algorithm based on UAV evaluations with respect to the determined features, Algorithm 1 has been applied for each of the main features. The input data for the FCM clustering algorithm has been given in Table 11 in the Appendix Section. Through Algorithm 1, considered vehicles have been assigned to determined clusters. For the prioritization of the clusters, the average value of the distances to the clusters has been calculated. Since these vehicles are currently operational on the ground, the cluster that has the minimum average value has been considered as the accomplished one, which means it has the first rank. Clusters have been prioritized based on these average values.

After the calculations for each of the main features, the number of clusters has been determined based on the MAE values and Elbow method. The MAE values based on the cluster numbers with respect to main features are presented in Table 5 as follows:

Elbow method has been used to determine the appropriate number of clusters which is presented in Fig. 2.

Through the determined numbers, clusters and membership value of the vehicles to those clusters have been obtained as in Table 6.

For the next phase, a rule-based system has been constructed based on the consensus evaluations. The constructed rule-based system has been given in Table 7.

After that, steps of Algorithm 2 are applied to obtain the final results. Through the calculations, the technology indices of the vehicles have been calculated as in Table 8.

Through the calculations, V6 has been determined as the first vehicle among the others. Six of the vehicles have values between five and six; therefore, they can be alternatives to each other in a cost-based system. Vehicles V5 and V7 are out of the contest compared to index values with the other six alternative UAVs.

4.1 A comparative analysis

Self-organizing map (SOM) and fuzzy k-means algorithms have been applied for the comparative analysis. To do that, each of the main feature datasets has been used as the inputs of the algorithms. Through the calculations, improvement rates on the errors of the algorithms have been calculated based on the number of clusters. The results obtained from the comparisons have been summarized in Table 9.

Based on the results, Fuzzy c-means has been determined as the most sensitive algorithm based on the improvement rate on the errors with respect to the number of clusters. By increasing the number of clusters, all algorithms performed the same pattern, which is decreasing the errors. Since the number of evaluated UAVs is equal to eight, overlapping values, especially starting from five clusters, are observed. This is another reason why the number of clusters is determined between the two and four for the features.

Comparison between SOM and fuzzy c-means algorithms yields that an increasing number of features increase the improvement rate on errors of the SOM algorithm better against the fuzzy c-means algorithm. Moreover, since the SOM algorithm assigns the samples to the clusters as 0 or 1, it may not reflect the nature of the application since the UAVs have similarities among them and are not fully distinguished. Fuzzy c-means algorithm outputs can perform clustering between not only 0 and 1 but also between the values of them. Moreover, this process is carried out by an objective function, which aims to minimize the distances of the samples to the cluster centers. Therefore, based on the distance, membership functions are calculated, and the clusters of the samples are determined. This is the most advantageous part of the fuzzy c-means algorithm against the SOM when the nature of the problem is considered.

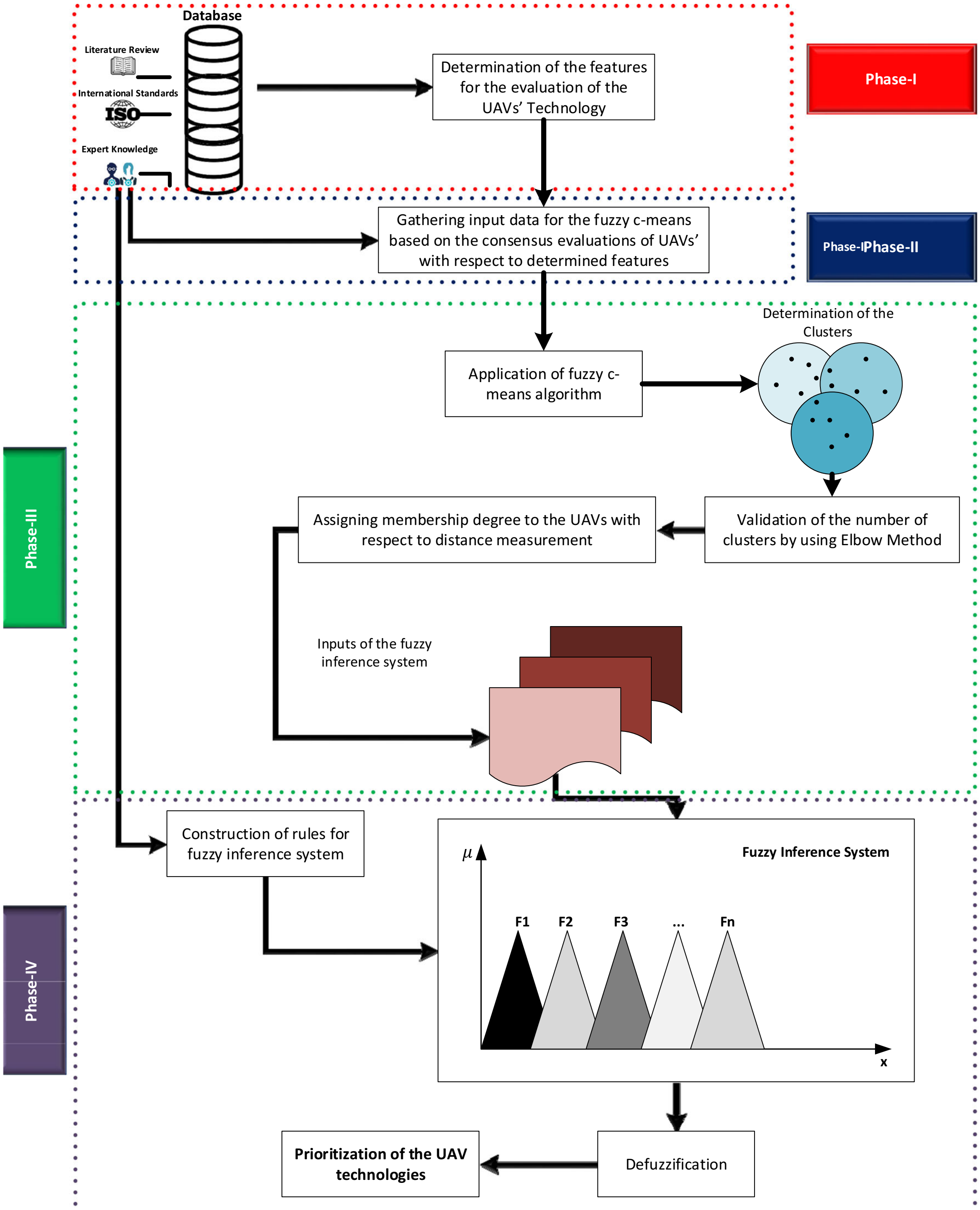

Fig. 1 Flowchart of the proposed methodology

Comparison between fuzzy k-means and fuzzy c-means algorithms are also considered to check the other parameters' effects on the objective function but the fuzziness. Based on the improvement rates on errors, the fuzzy c-means improvement rate increased more than the fuzzy k-means. When the initial mean absolute error (MAE) values are observed, fuzzy k-means started with a better MAE value than the fuzzy c-means. When the number of clusters is increased, fuzzy c-means is performed better than the fuzzy k-means. This may yield to the importance of the initial solution. For further research, the initial solution for the algorithms can be obtained by using a heuristic algorithm to check its effects on the iterations.

Table 3 Values for the sub-features of the F4-standard qualifications

Wingspan (meter)	Length (meter)	Payload capacity (kg)	Endurance (min)	Max cruise speed (knot)	Operational altitude (feet)
20	12.2	1350	1440	195	30,000
12	6.5	150	1620	120	18,000
2	1.2	10	80	40	2000
24	12	750	1440	97.192	7600
17	8	200	1920	117	300,000
7	6	80	720	108	12,000
1.5	2.3	10	60	400	15,000
10.5	6.5	70	1200	80	22,000

Table 4 Constructed linguistic scales for the subjective evaluations

Linguistic term	Abbreviation	Corresponded value	Linguistic term	Abbreviation	Corresponded value
Scale for F1-safety measures			*Scale for F2-cognitive functionality*		
Very reliable	VRa	1	Masterpiece	Mp	1
Reliable	Ra	0.8	Very Functional	VFn	0.8
Less reliable	LRa	0.6	Functional	Fn	0.6
Hazardous	Hd	0.4	Less Functional	LFn	0.4
Very hazardous	VHd	0.2	Ineffective	Iet	0.2
Fatal results	FRt	0	Inoperable	Ioa	0
Scale for F3-endurance to environmental conditions			*Scale for F5-national-level importance*		
Very high endurability	VHE	1	Outstanding	Osd	1
High endurability	HE	0.8	Critical	Crc	0.75
Average endurability	AE	0.6	Major Effect	MaE	0.5
Low endurability	LE	0.4	Minor Effect	MiE	0.25
Very low endurability	VLE	0.2	Negligible	Ng	0
Unendurable	Uea	0			

Table 5 Statistical results of the application based on the MAE values

Number of clusters	Objective function (MAE)	Number of clusters	Objective function (MAE)	Number of clusters	Objective function (MAE)
Safety measures feature		*Cognitive functionality feature*		*Endurance to EC feature*	
2	1.6735	2	3.7175	1	3.0567
3	**0.9452**	3	2.2202	2	1.9733
4	0.5553	**4**	**1.2397**	**3**	**1.2354**
5	0.2701	5	1.0409	4	0.7915
Standard qualifications feature		*National-level importance feature*			
1	2.9823	**2**	**1.4659**		
2	**0.3785**	3	0.8736		
3	0.1198	4	0.4754		
4	0.0563				

Bold lines demonstrate the determined number of clusters for the related features

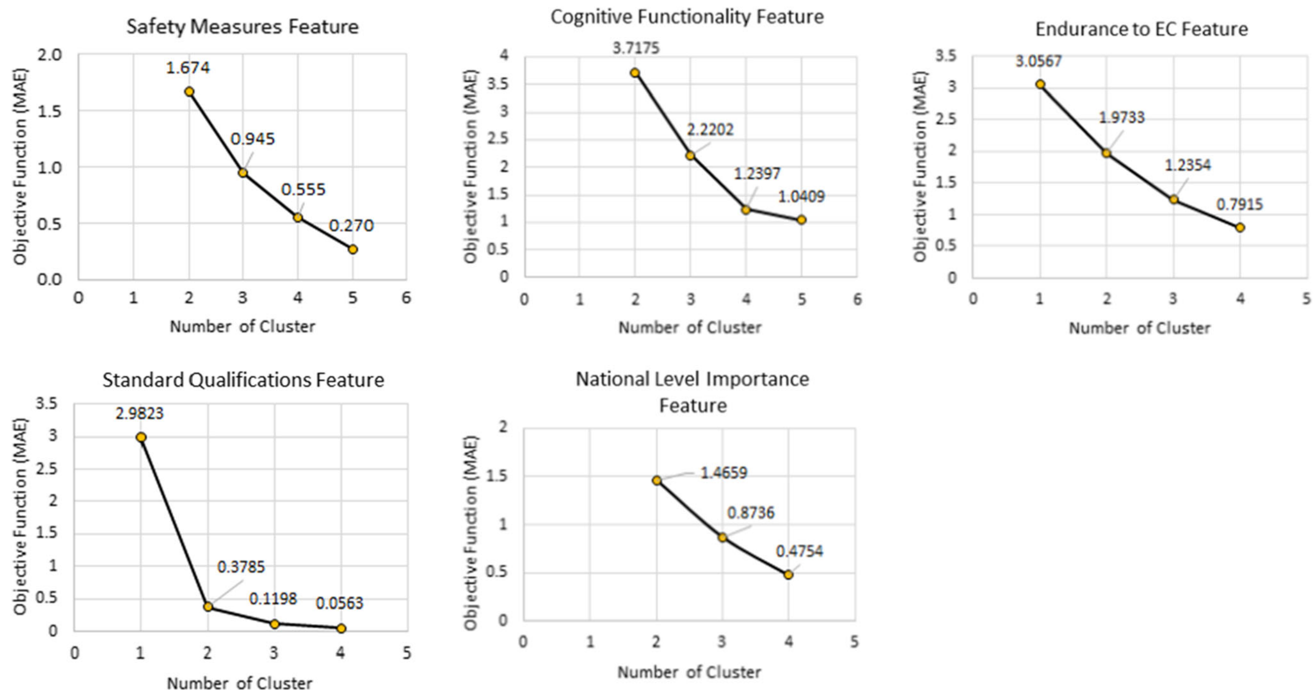

Fig. 2 Elbow charts of the main features with respect to MAE values of the clusters

Table 6 Determined clusters and membership values of the vehicles to these clusters

	C1: WQf	C2: Qf	C3: Acp		C1: LD	C2: D	C3: MD	C4: Acp
	wrt safety measures			*wrt cognitive functionality*				
V1	0.305	0.260	0.435	V1	0.198	0.218	0.222	0.362
V2	0.249	0.143	0.608	V2	0.162	0.159	0.502	0.177
V3	0.375	0.245	0.380	V3	0.146	0.149	0.200	0.505
V4	0.623	0.149	0.228	V4	0.113	0.728	0.079	0.080
V5	0.076	0.855	0.069	V5	0.170	0.162	0.190	0.478
V6	0.363	0.153	0.484	V6	0.119	0.118	0.600	0.163
V7	0.696	0.127	0.177	V7	0.790	0.086	0.063	0.061
V8	0.313	0.236	0.451	V8	0.227	0.264	0.254	0.255

	C1: D	C2: Md	C3: Acp		C1: Acc	C2: Acp		C1: Acc	C2: Acp
wrt endurance to environmental conditions				*wrt standard qualifications*			*wrt national-level importance*		
V1	0.224	0.346	0.430	V1	0.723	0.277	V1	0.353	0.647
V2	0.230	0.530	0.240	V2	0.256	0.744	V2	0.814	0.186
V3	0.145	0.678	0.177	V3	0.252	0.748	V3	0.462	0.538
V4	0.166	0.162	0.672	V4	0.680	0.320	V4	0.500	0.500
V5	0.588	0.208	0.204	V5	0.520	0.480	V5	0.568	0.432
V6	0.266	0.422	0.312	V6	0.117	0.883	V6	0.295	0.705
V7	0.412	0.268	0.320	V7	0.337	0.663	V7	0.384	0.616
V8	0.424	0.229	0.347	V8	0.177	0.823	V8	0.699	0.301

wrt: with respect to; Qf: Qualified; WQf: well-qualified; LD: Least Desirable; D: Desirable; MD: Most Desirable; Acc: Acceptable; Acp: Accomplished

Table 7 Constructed rule-based system based on the evaluations of the consensus

		EEC											
		D				Md				Acp			
		SQ											
		Acc		Acp		Acc		Acp		Acc		Acp	
		NL											
		Acc	Acp	Acc	Acp	Acc	Acp	Acc	Acp	Acc	Acp	Acc	Acp
SM	**CF**												
Qf	LD	VL	VL	VL	VL	VL	VL	VL	VL	L	L	L	M
	D	VL	VL	VL	VL	VL	VL	L	L	L	L	M	M
	MD	VL	VL	VL	VL	VL	L	L	L	L	M	M	M
	Acp	VL	VL	VL	VL	L	L	L	L	M	M	M	H
WQf	LD	VL	VL	VL	L	L	L	L	M	M	M	M	M
	D	VL	VL	L	L	L	L	M	M	M	M	M	M
	MD	VL	L	L	L	L	M	M	M	M	M	M	H
	Acp	L	L	L	L	M	M	M	M	M	H	H	H
Acp	LD	VL	VL	VL	L	L	L	M	M	H	H	H	H
	D	VL	L	L	L	M	M	M	H	H	H	H	VH
	MD	L	L	L	M	M	M	H	H	H	VH	VH	VH
	Acp	L	L	M	M	M	H	H	H	VH	VH	VH	VH

VL very low; *L* low; *M* medium; *H* high; *VH* very high

4.2 Discussion

Different simulations based on the different input values have been carried out for the system's performance in terms of robustness of the results. The indices based on the simulations have been calculated as seen in Table 10.

Based on the created artificial inputs, indices are gradually decreased except in one case, which is Simulation 2. The visual representation of the decrease can be observed in Fig. 3.

Through the results, inconsistency in the decrease is discussed with the experts. Since it is a small part of the rule-based system, it is neglected. Therefore, it is revealed that the hesitancy of the experts is also an issue to deal with in the system. Another issue is the prioritization of the clusters. Since the prioritization is based on the minimum average value of the distances of the vehicles to the clusters, we conducted simulations to observe the variations. In some of the simulations, it is observed that average values are very close to each other. In that case, prioritization of them is not applicable. In other words, both of the clusters are equal values based on our assumptions. Therefore, they can be of equal importance while constructing the rules in the rule-based system.

4.3 Managerial implications

The proposed methodology can be effectively used by the managers or R&D engineers to evaluate the UAV technologies to consider cardinal data and linguistic data. Since the constructed decision-making framework has a complex hierarchical structure, the results of the proposed decision-making model can be an efficient solution by combining different perspectives. Through the application, the below issues should be carefully investigated and decided.

Firstly, characteristics, which are expertise in the autonomous vehicles (also consisting of ground and marine vehicles), assignment for designing/buying/construction projects for the UAVs (before/ongoing), education level, job description in the company, privacy policies of the company (willing to share the information) are considered for the construction of the consensus. Regarding a UAV company, information about the design of the UAVs and their components (both hardware and software components) are highly confidential and prohibited to share. Therefore, the gathered information from the companies is quite limited. Based on that, in our application, the consensus has been constructed by involving academicians and researchers working in this area and specialists from the companies. We believe that, if the number of specialists from the company and the shared data will increase, the

Table 8 The obtained results of the application

	VL	L	M	H	VH	Index
V1	0.224	0.260	0.346	0.346	0.362	5.707
V2	0.230	0.249	0.256	0.502	0.240	5.532
V3	0.200	0.245	0.375	0.380	0.177	5.258
V4	0.166	0.166	0.500	0.228	0.228	5.464
V5	0.479	0.208	0.204	0.204	0.069	3.646
V6	0.153	0.266	0.363	0.422	0.312	5.830
V7	0.384	0.412	0.320	0.177	0.086	3.855
V8	0.236	0.264	0.264	0.264	0.264	5.290

applicability of the constructed context will also increase. Moreover, this also provides more robust and meaningful results.

The second issue is the construction of the rule-based system. Since the system's inputs are consisting of five main features, the consensus should consider them simultaneously while deciding the rules. Based on the discussions with the experts in the consensus, cognitive functionality is determined as the most crucial feature regarding the consisted sub-features. The sub-features of the cognitive functionality are based on the software qualifications. These sub-features also have an effect on the other sub-features, such as the ability to identify turbulence.

Moreover, standard qualifications are determined as the least important feature since most of the sub-features of it have no direct effect on operational processes of the UAVs such as Wingspan, Length. These features are mainly about the vehicle's visibility and center of gravity. Therefore, constructing a rule-based system is mainly based on the expert knowledge and the requirements of the decision-makers. In our system, the constructed context is for the military operations, which are surveillance of an area and counter-terrorism actions. For example, standard qualifications can be more important for a supply chain logistic system in which the vehicle transports the goods to the determined destination. In such a case, we believe national-level importance can be considered as out of context since the software dependability, hardware dependability, and international reputation are negligible in such a mission. But in a military context, these are crucial for a vehicle for the sustainability of the system and the averseness against the terrorist attacks and infiltration from the borders.

The last issue that needs to be explained is the absence of cost features in the constructed context. As a military operation, the most important issue is being killed or wounded in action. Through this, the vehicle's value does not matter when compared to the soldiers' or citizens' lives. But, at a realistic level, purchasing power or construction power is also an important issue. Therefore, our system provides technology indices of the UAVs to prioritize them with no cost feature to enable companies/institutions to decide according to their budget.

The limitations of this study can be summarized based on the above-mentioned issues. The analysis is performed for eight UAVs produced in Turkey by four military companies. Through this concept, the consensus origin is selected as Turkey to reflect the study's environment better. Through that, for a comparison with other military UAVs in the market, a new consensus should be organized by

Table 9 Results of the comparisons based on the improvement rate on errors

Cluster	Improvement rate on errors			Cluster	Improvement rate on errors		
	SOM	Fuzzy c-means	Fuzzy k-means		SOM	Fuzzy c-means	Fuzzy k-means
Results based on safety measures feature				*Results based on cognitive functionality feature*			
From 2 to 3	26%	44%	12%	From 2 to 3	32%	40%	5%
From 3 to 4	21%	41%	6%	From 3 to 4	53%	44%	8%
From 4 to 5	33%	51%	31%	From 4 to 5	31%	16%	26%
Total improvement	79%	136%	49%	Total improvement	116%	100%	39%
Results based on cognitive functionality feature				*Results based on cognitive functionality feature*			
From 2 to 3	29%	37%	4%	From 2 to 3	52%	68%	3%
From 3 to 4	36%	36%	4%	From 3 to 4	47%	53%	18%
Total improvement	65%	73%	8%	Total improvement	99%	121%	21%
Results based on cognitive functionality feature							
From 2 to 3	48%	40%	4%				
From 3 to 4	43%	46%	12%				
Total improvement	92%	86%	15%				

Table 10 Input values and the calculated indexes based on the simulations

	SM			CF				EEC			SQ		NL		Index
	Qf	WQf	Acp	LD	D	MD	Acp	D	Md	Acp	Acc	Acp	Acc	Acp	
S1	0	0	1	0	0	0	1	0	0	1	0	1	0	1	10.00
S2	0	0.10	0.90	0	0	0.10	0.90	0	0.10	0.90	0.10	0.90	0.10	0.90	8.75
S3	0.05	0.05	0.90	0	0.05	0.05	0.90	0.05	0.05	0.90	0.10	0.90	0.10	0.90	8.91
S4	0.05	0.10	0.85	0	0.05	0.10	0.85	0.05	0.10	0.85	0.15	0.85	0.15	0.85	8.38
S5	0.85	0.10	0.05	0.85	0.10	0.05	0	0.85	0.10	0.05	0.85	0.15	0.85	0.15	2.17
S6	0.90	0.05	0.05	0.90	0.05	0.05	0	0.90	0.05	0.05	0.90	0.10	0.90	0.10	1.94
S7	0.90	0.10	0	0.90	0.10	0	0	0.90	0.10	0	0.90	0.10	0.90	0.10	1.55
S8	1	0	0	1	0	0	0	1	0	0	1	0	1	0	1.00

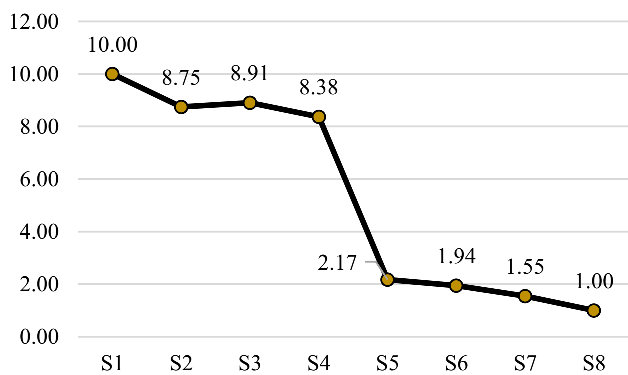

Fig. 3 Visual representation of the variation in indexes for simulations

involving experts from both origins. Another issue can be the evaluations of the experts. As in human nature, hesitancy in all decisions can be observed at different levels. In this study, the expert evaluations are considered without indeterminacy, which means they fully ensured their evaluations. This impression concludes based on the crosscheck evaluations.

Based on the constructed context, we believe that the proposed methodology can be an efficient evaluation process as a decision-making tool by the managers or researchers to make valuable inferences, judgments, and decisions for prioritizing the UAVs by considering their technology levels. Since the model considers both cardinal and linguistic data, it can be a good way of representing uncertainty in the decision-making processes.

5 Conclusions

UAVs are vehicles that can fly on a path by directly programming or remotely operating. UAVs are divided into three categories in terms of their various uses: military, scientific research, and commercial applications. Popular applications include traffic monitoring, monitoring and surveillance, remote sensing, crop monitoring, and search and rescue activities. In this study, the constructed framework concerns military applications by considering different perspectives based on the available cardinal data and knowledge of academicians and specialists from the field.

When addressing the growing uses of UAVs, some technical and non-technical features of this technology need to be considered. UAV technologies are distinguished according to various features based on addressing problems. In this study, apart from the features assigned with cardinal data such as weight, altitude, endurance, and speed, the features that can be evaluated with a scale consisting of linguistic terms are considered. An integrated methodology involves FCM clustering, and FIS has been proposed to evaluate and prioritize the UAV alternatives with this perspective. Eight UAVs that are used for military applications produced in Turkey have been specified as alternatives. For the evaluation process, five main features have been determined as “Safety Measures”, “Cognitive Functionality”, “Endurance to Environmental Conditions”, “Standard Qualifications”, and “National-level Importance” that are coded respectively as F1, F2, F3, F4, and F5. Besides, thirty-one sub-features have been adopted under these main features to evaluate the UAV technologies. In light of this information, technology indices have been obtained to prioritize the alternative UAVs. Moreover, different scenarios have been simulated to check the robustness of the proposed methodology. Through the results and discussions, managers and researchers can make helpful inferences by using the proposed methodology for prioritizing UAVs by considering the constructed context.

For further studies, the constructed system can be adapted to supply chain systems. In that case, the constructed feature hierarchy can be changed based on the requirements of a supply chain system. Moreover, multi-expert-based data can be conducted. The experts can be divided into groups based on academicians, researchers, and engineers from the field. Based on their perspectives, a roadmap for the evaluations can be constructed.

Furthermore, a new function to handle the hesitancy of the experts can be conducted for the application. Through that, the membership function and hesitancy function can be fused into the methodology to obtain the aggregated value of the evaluations. A threshold value can also be determined for the hesitancy function. For the assessments with a lower value of the threshold, they can be neglected.

Appendix

See Table 11.

Table 11 Evaluations of the consensus with respect to main features for the determination of the clusters for fuzzy c-means clustering

	F21	F22	F23	F24	F25	F26	F27	F28	F29	F210		F51	F52	F53	F54
V1	Iet	VFn	Mp	LFn	Iet	Iet	LFn	LFn	LFn	VFn	V1	Crc	Ng	MiE	Crc
V2	LFn	LFn	VFn	LFn	VFn	VFn	Mp	Iet	LFn	LFn	V2	Crc	Osd	MaE	MaE
V3	Iet	VFn	Mp	LFn	VFn	Iet	Ioa	Ioa	VFn	Mp	V3	Ng	MaE	MiE	MiE
V4	Mp	Mp	Fn	Fn	Ioa	Iet	Fn	Fn	VFn	Iet	V4	Osd	MaE	Ng	Crc
V5	Ioa	Mp	LFn	VFn	Fn	LFn	Iet	Iet	Fn	Mp	V5	Crc	Crc	Crc	Ng
V6	LFn	Iet	VFn	Fn	Mp	LFn	Fn	Ioa	Fn	LFn	V6	Crc	Ng	MaE	Ng
V7	VFn	VFn	Ioa	Iet	Ioa	Iet	Fn	Ioa	LFn	LFn	V7	Osd	MiE	Crc	MiE
V8	Mp	Ioa	Iet	Mp	VFn	Ioa	Iet	Mp	VFn	Mp	V8	Osd	Osd	Crc	Crc

	F11	F12	F13	F14	F15		F31	F32	F33	F34	F35
V1	LRa	VHd	VRa	Hd	FRt	V1	HE	LE	Uea	HE	LE
V2	VRa	VHd	Hd	LRa	LRa	V2	AE	VHE	AE	AE	LE
V3	LRa	Hd	LRa	Hd	Ra	V3	VLE	VHE	VLE	AE	AE
V4	VHd	VHd	FRt	VHd	LRa	V4	AE	VLE	Uea	VLE	HE
V5	Hd	VRa	VRa	FRt	VRa	V5	VLE	LE	VHE	VLE	VHE
V6	Ra	VHd	FRt	LRa	Hd	V6	Uea	AE	VLE	LE	HE
V7	Hd	Hd	VHd	VHd	Ra	V7	Uea	Uea	AE	Uea	VLE
V8	VRa	LRa	Hd	FRt	VHd	V8	VHE	Uea	HE	Uea	HE

F1 Feature for safety measures; *F2* Feature for cognitive functionality; *F3* Feature for endurance to environmental conditions; *F5* Feature for national-level importance; *V* vehicle

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Declarations

Conflict of interest All authors state that there is no conflict of interest.

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