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Identifying Critical Factors for Implementing Unmanned Aerial Vehicle in Warehouse using a Newly Hybrid Decision-Making Method

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) have been extensively utilised in the domain of Supply Chain Management. Nonetheless, its implementation in warehouse management is nascent, and the impact of UAV adoption requires thorough investigation. The effective execution of this novel technology relies on several significant elements that necessitate methodical methods and methodologies for a more accurate analysis. This study seeks to determine essential parameters for the implementation of UAVs in warehouse management. The proposed method amalgamates the Delphi technique, best-worst method, decision-making trial and evaluation laboratory, and analytic network process to enhance the shortcomings of conventional and advanced multi-criteria decision-making approaches. Two primary components, Operation and Technology, along with 10 subordinate factors, were identified. The method was utilised to identify the most significant factor influencing UAV adoption in warehouse management, establishing a basis for future research and practitioners to focus on these issues.

1. Introduction

In contemporary business and supply chain management, the warehouse plays a crucial role at both the organizational and supply chain levels, primarily overseeing the receipt, picking, storage, and dispatch of inventory. Given the increasing competition within the business landscape, many organisations are focusing on enhancing and refining warehouse management processes to strengthen their competitive advantage and ensure long-term sustainability. One such innovative technology, the UAV, or drone, has been recognised for its potential to significantly improve the effectiveness and efficiency of logistics and warehouse operations [33].

UAVs have gained widespread application in both academic research and practical settings. As noted by Cho et al. [5], UAVs can support operational tasks and effectively manage large warehouses. The integration of UAVs into warehouse operations has been shown to significantly

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enhance the speed of stock counting, with UAVs completing tasks up to 100 times faster than traditional methods. Similarly, inventory tracking via drones can process over 1,500 labels per hour, which is 3.75 times more efficient than manual counting using handheld RFID technology [22]. While the adoption of UAVs in warehouse management offers clear advantages for organisations, their successful implementation in real-world settings requires further improvement. Achieving optimal performance from UAVs hinges on several critical factors (CFs) [23], making the identification and understanding of these factors essential for successful integration into warehouse operations.

Most existing studies have primarily focused on the development and potential improvements of UAV implementations in warehouse operations [5; 33]. However, these studies often lack specificity and prioritisation of the CFs that directly influence the success of new technology adoption within organisations [1]. Given the gaps in previous research, it is crucial to identify the CFs associated with UAV adoption in warehouse management. Accordingly, this study seeks to identify these CFs and examine their practical benefits for both academic and commercial sectors. We have systematically prioritised the identified CFs to assist researchers and practitioners in effectively selecting and managing these factors within the constraints of limited resources and organisational budgets.

To achieve the objectives outlined, this study introduces a novel hybrid decision-making method tailored to the specific needs of the research. The proposed method integrates four decision-making approaches: Delphi, the Best-Worst Method, Decision-Making Trial and Evaluation Laboratory [31], and the ANP. Experts and scholars in relevant fields contributed to the identification and prioritisation of CFs. The structure of the paper is as follows: Section 2 reviews the literature on CFs related to UAV adoption in warehouse management and hybrid decision-making methods; Section 3 outlines the methodology of the proposed model; Section 4 demonstrates the feasibility of the method through a case study; and Section 5 concludes with a summary of the key factors and recommendations for future research.

2. Literature Review

This section provides a comprehensive overview of the background, past developments, and opportunities for improvement by reviewing the literature on the CFs influencing UAV adoption in warehouse operations, as well as the hybrid decision-making methods used to identify and prioritise these factors.

2.1 The CFs of UAV Adoption in Warehouse Management

Malang et al. [18] highlighted the lack of studies specifically addressing the CFs of UAV adoption in warehouse management. Through an extensive review of 104 relevant articles, they identified and classified the CFs into five main categories: technology, operations, organization, legislation and standards, and society and mentality, as illustrated in Figure 1. The first major CF, technology, encompasses three sub-factors: hardware, software, and integrated systems and others. In the context of warehouse tasks, one of the key challenges is that drones are unable to precisely navigate and localise their positions indoors using global positioning systems (GPS) and global navigation satellite systems (GNSS), which are typically relied upon for outdoor navigation.

To address the indoor navigation challenge, several past studies have focused on the development and improvement of UAV hardware components. Among the most recommended improvements are optical and camera-based sensors, as well as light detection and ranging (LiDAR) technology. Additionally, two hardware elements, namely warehouse hardware and communication networks, have been frequently suggested for enhancement. Regarding the software sub-factor, recommendations have been made to address indoor navigation issues and optimise organisational resources. Three types of software algorithms have been proposed: (1) scheduling and path planning algorithms, (2) localisation and navigation algorithms, and (3) warehouse management algorithms, such as barcode detection and object recognition. These advancements aim to improve UAV efficiency and effectiveness in warehouse environments.

The final sub-factor of technology, integrated systems, refers to the collaboration of various systems and technologies, such as UAVs and RFID [11], aerial vehicles (AVs) and automated guided vehicles (AGVs) [28], or UAVs and block chain [3]. The integration of these systems is recommended to address the complex operational requirements of both warehouse management and drone missions. The second major critical factor, operations, comprises seven sub-factors: (1) area or distance of operation, (2) mission time, (3) costs, (4) drone operation, (5) warehouse operations, (6) environment, and (7) item or inventory. These factors are crucial for optimizing UAV performance in warehouse settings and ensuring efficient operations. Among the various sub-factors, the area or distance of operation is the most frequently highlighted within the operational category. This factor significantly influences the success of UAV adoption in warehouses, impacting aspects such as the number of UAVs in operation, drone speed, delivery time, and battery size.

Mission time is another critical determinant of UAV utilization success. Several studies have proposed approaches to reduce mission time, including expanding the drone fleet, increasing UAV speed, reducing energy consumption, and optimizing UAV paths and schedules. The third sub-factor, operational costs, is a fundamental consideration for businesses and warehouses. While many studies have identified the overall costs of operations as a critical factor, few have specifically addressed the types of costs involved, such as UAV hardware, inventory, and maintenance expenses. These detailed cost considerations are essential for the effective implementation of UAVs in warehouse operations.

The operation of drones is one of the most frequently mentioned sub-factors within the operational category, encompassing aspects such as the number of UAVs in operation, drone control, and breakdowns. In contrast, the warehouse operational factor addresses the compatibility between warehouses and UAVs, the types of warehouses and their characteristics, and the warehouse processes involved. Environmental conditions, such as light, noise, humidity, and climate, are identified as direct influences on UAV performance. These environmental factors can significantly affect the operational efficiency and success of UAV adoption in warehouse settings. Inventory items, the final sub-factor of operations, focus on two primary aspects: the number of items and their weight and size. These factors are crucial for determining the feasibility and effectiveness of UAVs in managing warehouse inventories.

Organizational factors also play a role in UAV adoption, primarily through the organization’s general processes. Past studies have highlighted two key aspects: firms' budgets and organizational maintenance systems. The fourth major factor, legislation and standards, is relatively under-explored in the literature. However, there is a growing recognition of the need for regulations and standards governing UAV operations in indoor warehouses and private locations. Such legislation is essential for enhancing user confidence and ensuring industry acceptance of UAV technology. Finally, the societal and mental factor focuses on the impact of UAV adoption on the perceptions and mental attitudes of stakeholders and the broader society. This factor emphasizes the importance of addressing the legal and psychological dimensions to improve public trust and ensure the protection of all parties involved in UAV operations.

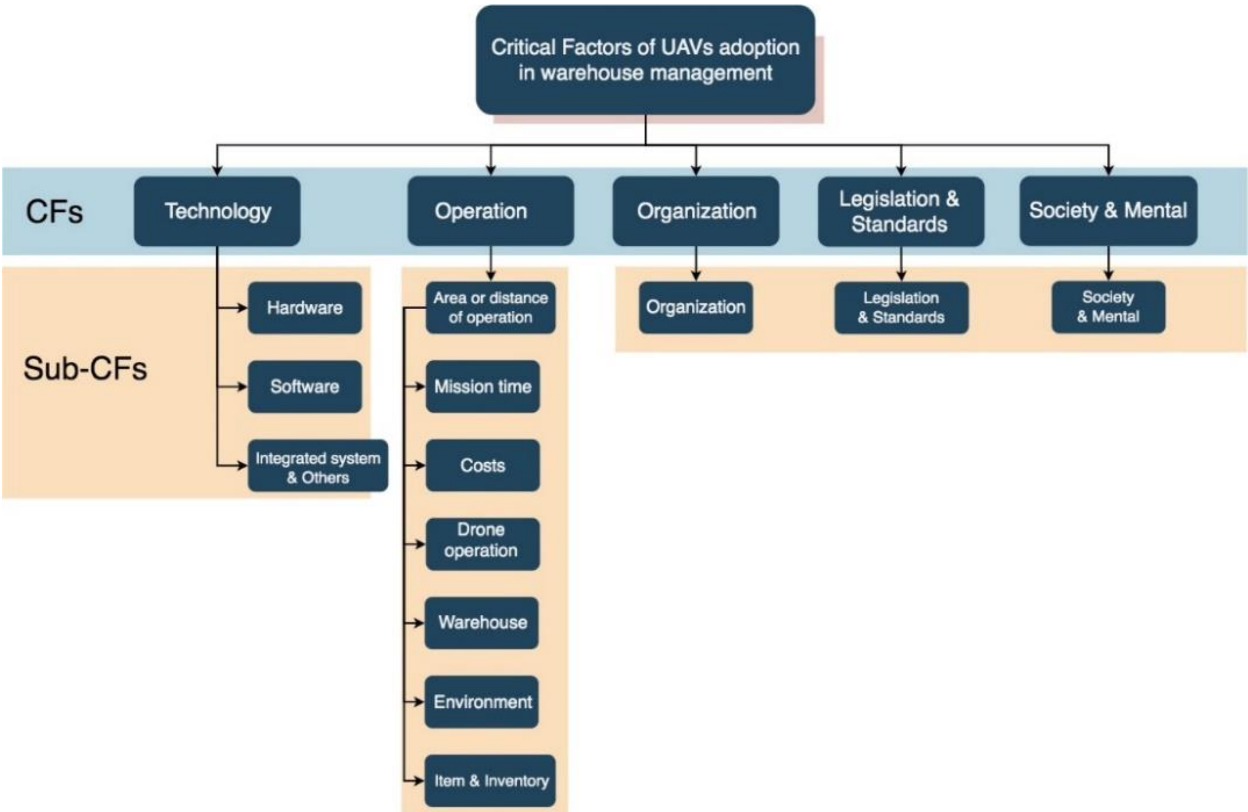

Fig. 1. Lists of CFs and Sub-CFs of UAV Adoption in Warehouse Management

2.2 The Hybrid Decision Making Method for Selecting and Prioritizing UAV Factors

The adoption of multi-criteria decision-making (MCDM) methods for selecting or prioritizing factors has been extensively studied across various fields. However, the prioritization of UAV-related factors, specifically in warehouse management, remains an underexplored topic. To date, only four studies [7; 8; 12]have concentrated on UAV-related factors, yet none of these studies have addressed the key success factors for UAV adoption in warehouse management. Among these, two studies employed MCDM methods: (1) AHP and TOPSIS [7], and (2) fuzzy AHP [10] to priorities UAV factors in military and defense operations. One study examined factors related to civilian-use UAVs using an adapted AHP method. However, AHP has been criticized for its fundamental limitation, notably its failure to account for the relationships between sub-criteria [29].

To address the limitations of AHP, the ANP was developed by Thomas Saaty [30]. The ANP method has been widely applied across various research fields [2; 16; 34]. However, it remains infrequently used for prioritizing UAV factors, despite the clear interdependencies between various drone operational factors. Given these interrelations, the adoption of ANP appears necessary for this area of study [12]. Notably, only one study by Kamat et al. [12] applied ANP in combination with another MCDM method to prioritize factors in humanitarian logistics. To date, there has been no scientific research focusing on the prioritization of factors influencing the adoption of UAVs in warehouse management.

The successful implementation of UAVs in warehouse operations is closely tied to the prioritization of factors influencing their adoption. Many past studies applying AHP overlooked the key characteristics of UAVs. The results derived from AHP should focus on identifying the correct priorities for UAV-related factors. One study integrated MCDM to address this issue; however, MCDM still presents two main limitations: (1) an unsystematic process for the initial selection of factors, and (2) the inclusion of too many factors in the prioritization process. The first limitation leads to inconsistent decision outcomes, particularly when consensus among the expert group is difficult to achieve. Several studies have sought to resolve this issue by incorporating additional decision-making methods, such as the Delphi technique. The Delphi method has been integrated into MCDM processes to support the systematic selection of attributes considered relevant to the problem at hand [14; 15; 19]. This approach enhances the decision process by ensuring a more systematic approach to initial screening and by mitigating biases that may arise from individual experts' opinions.

The second flaw in MCDM methods, involving excessive time and resource consumption when dealing with numerous factors, has been addressed through the application of the Best-Worst Method (BWM). BWM helps filter a large number of criteria or attributes to a manageable level. However, the integration of this method in UAV studies remains limited. Only two studies have applied this integrated approach to weight UAV-related factors, but these studies primarily yielded biased results, largely due to individual decisions. Some efforts have been made to combine BWM with other decision-making methods, such as the Delphi technique. While many studies have applied Delphi and BWM separately, their integration is rare in recent research. Moreover, there is a lack of integrated solutions for addressing the two main issues identified in the adapted MCDM process. A related approach integrated DEMATEL, BWM, and ANP Liu et al. [17], offering a solution for some fundamental decision-making challenges. However, this approach lacks a systematic group decision-making process for the initial selection of criteria and consumes significant time in identifying relationships among criteria after they have been eliminated.

To address these issues and reduce bias from individual experts, this study proposes an integrated approach that combines the Delphi technique with BWM, rearranging the processes to use BWM before DEMATEL and ANP. This approach aims to improve the decision-making process by ensuring more systematic group input and optimizing time and resource use in the prioritization of UAV adoption factors. The details and procedures of the proposed method are presented in the following section.

3. Materials and Methods

The formulation of the research methodology is predicated on the enhancement of the fundamental constraints of previous methodologies. This research adheres to the integrated methodology proposed by [17]. We enhance the prioritization process and incorporate the Delphi approach. The comprehensive procedures of the newly proposed approach are depicted in Figure 2. Figure 2 illustrates that the suggested hybrid decision-making process amalgamates four approaches: the Delphi technique, BWM, DEMATEL, and ANP. The details of four principal steps are elucidated as follows.

3.1 Initial Identification of CFs of UAV Adoption in Warehouse Management using Delphi Technique

The identification of CFs arises from the determinations of multiple field specialists through the Delphi method, which can be categorized into four stages.

3.1.1 Identify a Problem and Expert in the Field

This stage seeks to elucidate the issue being examined. A well-defined research topic and objectives are utilized to ascertain the criteria or credentials of specialists. The number of specialists in the survey panel is ten or more.

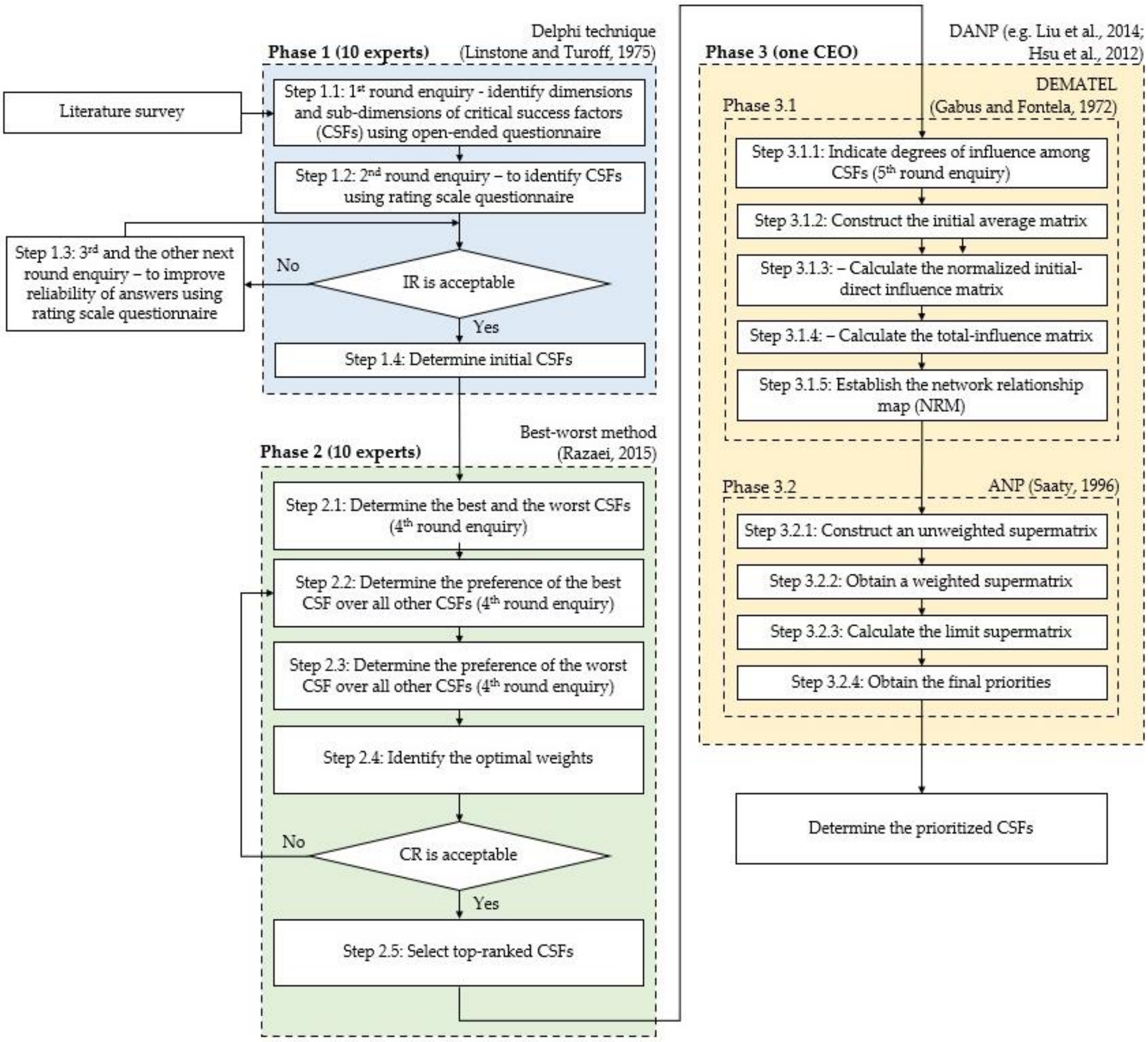

Fig.2. The Overall Processes of the Proposed Method

3.1.2 The First-Round Inquiry

The first-round inquiry is conducted through an open-ended questionnaire designed to provide broad questions to experts while ensuring that all relevant issues are covered. The results obtained from this initial round must be carefully analyzed, summarized, and used to refine and develop the second-round questionnaire. This iterative process ensures that the criteria and factors considered are relevant, comprehensive, and aligned with the objectives of the study, allowing for more focused and specific input in subsequent rounds of expert consultation.

3.1.3 The Second-Round Inquiry

The second-round enquiry is conducted via a questionnaire developed based on the results from the preceding enquiry. Respondents are asked to evaluate the significance of the CFs using a five-point Likert scale. The responses are then analyzed to calculate the median and interquartile range (IR) values. For a CF to be selected for further analysis, its median must be equal to or greater than 4.50, and its IR value must be equal to or less than 1.00 [24; 26].

3.1.4 The Third-Round Inquiry

The third-round and subsequent round enquiries are conducted if the IR results remain unacceptable. These rounds follow a process similar to the second round, with the aim of improving the consistency of the experts' responses or achieving acceptable IR values. The enquiry process will continue until all IR values meet the required criteria.

3.1.5 Conclusion of Delphi Results

The consistent results are utilized to identify the initial CFs. These extracted factors are then prioritized using other methods in the subsequent stages of the process.

3.2 Filtering CFs using BWM

3.2.1 Identifying the Best and Worst CFs

The BWM is employed to filter the CFs identified in the Delphi approach. In this step, experts with extensive experience in UAV adoption and/or warehouse management are asked to select the best and worst CFs from the first major stage.

3.2.2 Comparing the Worst CF with all Other Factors

This phase evaluates and contrasts the most unfavorable CF against all other CFs utilizing the 1-to-9 rating system. “One” indicates that the relevance of the compared component is equivalent to that of the least significant element, while “nine” denotes that the compared factor is considerably more significant than the least significant factor.

3.2.3 Comparing the Best CF with all Other Factors

In this step, the best CF is compared with all other CFs. A rating of "one" is assigned when the compared factor is considered equally important to the best factor, while a rating of "nine" signifies that the best factor is deemed significantly more important than the compared factor.

3.2.4 Calculating Weights of all CFs

Calculating weights of all CFs using the linear model, as shown in Eq. (1),

$$
\begin{aligned}
&min\, \xi \\
&s.t \left|\frac{w_B}{w_j} - a_{B_j}\right| < \xi; f\ or\ all\ j \\
&\left|\frac{w_j}{w_W} - a_{jW} < \xi; f\ or\ all\ j\right| \\
&\sum_j w_j = 1 \\
&\quad w_j > 0; f\ or\ all\ j,
\end{aligned}
\tag{1}
$$

WB denotes the weight of significance of the optimal component, while WW represents the weight of significance of the suboptimal element. The final weights are derived from the average values of the factors' weights obtained from several responses. Weights of significance are utilized to prioritize CFs. Consequently, the initial ten rankings of components are chosen for subsequent analysis.

3.3 Identifying Relationships between Factors with DEMATEL Method

The chosen CFs from the preceding stage are evaluated for their interconnections. This method is essential as the connections among elements are a fundamental attribute of strategic and tactical management. The interconnections among CFs directly influence the significance, weight, and priorities of each component. A component that significantly influences others, whether positively or negatively, will possess greater importance than one that does not impact others. This study employs DEMATEL as MCDM can ascertain both associations and their strengths [32]. DEMATEL is the appropriate strategy for examining relationships and independence among a limited set of components [9]. It is utilized to ascertain relationships amongst CFs and their related magnitudes. A senior manager from the warehouse, possessing expertise in drone implementation, is solicited for their insights. The subsequent sub-steps are performed to analyses and acquire data in accordance with the DEMATEL protocol.

3.3.1 Identifying Relationships and Influences between Factors by Expert

The identifying technique adhered to the comparative scales outlined in a systematic questionnaire. In the case of several involved experts, the obtained comparison results from each expert are applied for constructing a $n \times n$ matrix (n is a number of criteria of study), which can be presented in the form of matrix $X^k = \left[x_{ij}^k\right]_{n\,x\,n}$, where k is an expert with $1 \leq k \leq H$, and H is a number of experts.

3.3.2 Constructing the Initial Direct-Relation Matrix and the Normalized Initial Direct-Relation Matrix

The results generated from the preceding phase are utilized to compute an initial direct-relation matrix or an average matrix (matrix A), in accordance with Eq. (2).

$$A = \frac{1}{H}\sum_{k=1}^{H}\left[x_{ij}^k\right]_{n\,x\,n} \tag{2}$$

The highest value chosen from the aggregated values of each row of matrix A (s) is utilized to normalize matrix A. The procedure for building the normalized initial direct-relation matrix (matrix D) must be executed, since it can be computed using Eq.(3).

$$D = \frac{A}{S} \tag{3}$$

Where s = max $\left(\max_{1\leq i\leq n}\sum_{j=1}^{n} a_{ij}, \max_{1\leq j\leq n}\sum_{j=1}^{n} a_{ij}\right)$.

3.3.3 Constructing the Total Relation Matrix

We utilized the normalized initial direct-relation matrix from the preceding stage to construct the total relation matrix. The (T) may be expressed in Eq. (4).

$$T = D + D^2 + D^3 + D^n = D(1 - D)^{-1} \tag{4}$$

Where I is identity matrix, the total relation matrix can be used for calculating the dispatcher and receiver groups. The identifications of these clusters start from computing the summation of values in each column (c_j) and each row (r_i) of matrix T. When j=i, the sum of (r_i + c_i) represents the total effects of caused and received by criterion i. (r_i + c_i) represents the degree of importance that criterion i contributes to the system, whereas ($r_i - c_i$) shows the net effect that criterion i contributes to the system. When the value of ($r_i - c_i$) is positive, it means the criterion i is a net dispatcher. However, when the value of ($r_i - c_i$) is negative, the criterion i is a net receiver [29].

3.3.4 Constructing the Network Relationship Map (NRM) between Criteria

A threshold value is established by calculating the average values of all members in the total relation matrix. The results are then used to construct a causal diagram, which is divided into two axes. These axes represent the various relationships between criteria, with one axis reflecting the causes and the other reflecting the effects, allowing for a clearer understanding of the interactions within the system. Such as (1) a horizontal axis indicating ($r_i + c_j$), and (2) a vertical axis indicating ($r_i - c_j$). However, only criteria or factors with influence levels greater than the threshold value are selected and displayed in the NRM.

3.3.5 Constructing the Normalized Total Relation Matrix

This step identifies the key factor weights before integrating with the ANP, offering a more accurate representation of real-life situations compared to traditional MCDM methods. The normalized total relation matrix is calculated using the previous section's matrix and a threshold value. Values below the threshold are reset to zero. Each row of the resulting matrix is normalized by the total of its row. The outcomes are then used to determine the weights and priorities of factors through integration with the ANP.

3.4 Indicating the Weights of Factors and their Priorities through the ANP Method

The main limitation of ANP using reciprocal values is its inability to accurately determine cluster weights in real-world situations [30]. To address this, some DEMATEL outputs are integrated with the ANP. The details of the adapted ANP are outlined below.

3.4.1 The Construction of Unweighted Super Matrix and Weighted Super Matrix

The unweighted and weighted super matrices are derived using the traditional ANP method through pairwise comparisons, with further details provided in [29]. The general form of the unweighted super matrix is shown in Eq. (5).

$$W = \begin{array}{r} e_{11} \\ e_{12} \\ c_1 \ \vdots \\ e_{1m_1} \\ e_{21} \\ e_{22} \\ c_2 \ \vdots \\ e_{2m_2} \\ \vdots \ \ \vdots \\ e_{n1} \\ e_{n2} \\ c_m \ \vdots \\ e_{nm_n} \end{array} \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ & & \cdots & \\ & & \cdots & \\ \vdots & \vdots & \cdots & \vdots \\ & & \cdots & \\ w_{n1} & w_{n2} & \cdots & w_{nm} \end{bmatrix} \quad (5)$$

Where c_m denotes the mth major factor, e_{nm} is the mth sub-factor in the nth major factor. Wij is the principal eigenvector of the influence of the sub-factors in the jth major factor compared to the ith major factor. To obtain the weighted super matrix, the normalized total relation matrix from the DEMATEL process is multiplied by the unweighted super matrix of the ANP.

3.4.2 The Calculation of Limit Super Matrix and the Identification of Weights of Factors

The limit super matrix is obtained by raising the weighted super matrix to limiting powers, following the traditional ANP approach. Eventually, the values in each column converge, representing the importance weights of the corresponding factors. These values are then used to priorities the factors and inform the final analysis.

4. Results and Discussion

The research procedure has been applied to a real case of selecting and prioritizing CFs for utilizing UAVs in warehouse management. This section outlines the implementation details to illustrate the proposed methodology.

4.1 Delphi-Based Technique for Identifying the Initial Set of CFs

In the first stage of the Delphi technique, ten experienced experts provided their opinions on the CFs for UAV adoption in warehouse management. The qualifications of the experts are shown in Table 1. Most experts had over five years of experience, with 40% having direct experience with UAV adoption in warehouse activities or related projects, 30% being UAV experts in other fields, and 30% possessing knowledge of UAV systems without direct experience. In the first-round enquiry, experts were asked to identify CFs using an open-ended questionnaire. These CFs were summarised into five major CFs (MCFs) and 17 sub-factors (SCFs), which were then used in a second-round questionnaire. Experts rated the significance of the CFs on a 1-to-10 scale, following the Delphi approach.

Table 1
Knowledge and Experience of Experts Participating in the Study

Expert	Management Level	Experience / Knowledge Warehouse Management	Drone Application in Warehouse Management
Expert 1	Top	More than Ten Years	Direct Experience
Expert 2	Top	Between Five to Ten Years	
Expert 3	Middle	Between Five to Ten Years	
Expert 4	Middle	Between Five to Ten Years	
Expert 5	Middle	Between Five to Ten Years	Indirect Experience
Expert 6	Middle	Between Five to Ten Years	
Expert 7	Middle	Between Five to Ten Years	
Expert 8	Middle	Between Five to Ten Years	No Experience, but Knowledgeable
Expert 9	First-Line	Between Five to Ten Years	in UAV Operations or Systems
Expert 10	First-Line	Lower Than Three Years	

Most expert responses were congruent, though some inconsistencies were noted in a few CFs. Experts were asked to reassess their ratings in the third-round enquiry, using additional data (e.g., median values, first and third quartile values). In the end, all responses aligned, meeting the acceptable level (IR<1.00). The selected CFs, four major factors, and 13 sub-factors (Median>4.5) with significant results are summarised in Table 2.

Table 2
CFs of UAV Adoption in Warehouse Management Obtained from Delphi Technique

CFs	Acronym	Type of CFs*		Median	IR
		MF	SF		
Technology	MCF1	✓		4.5	1
Hardware	SCF1		✓	4.5	1
Software	SCF2		✓	5	0.75
Integrated Systems	SCF3		✓	5	0
Compatibility and Completeness	SCF4		✓	5	0.75
User Friendly	SCF5		✓	5	1
Operation	MCF2	✓		5	0.75
Area or Distance of Operation	SCF6		✓	5	0

Table 2
CFs of UAV Adoption in Warehouse Management Obtained from Delphi Technique(cont…)

CFs	Acronym	Type of CFs* MF	SF	Median	IR
Mission Time	SCF7			4	1
Costs	SCF8			5	1
Drone Operation	SCF9			5	1
Warehouse	SCF10			4.5	1
Environment	SCF11			4	1
Items and Inventories	SCF12			4.5	1
Organization	MCF3			4.5	1
Budgets	SCF13			5	1
Maintenance System	SCF14			4.5	1
Legislation and Standards	MCF4			4.5	1
Standard Systems	SCF15			5	1
Laws and Regulations	SCF16			4	0.75
Society and Mental	MCF5			4	1
Mental of Stakeholders	SCF17			4	0.75

4.2 BWM-Based Technique for Filtering Related CFs

In this stage, experts continued to screen the CFs from the previous step. They were asked to identify the best and worst factors before comparing them to all others. Comparisons were made at the sub-factor level, as the filtered SCFs would directly influence the selection at the major factor level, as shown in Table 3. Moreover, the results were used to calculate the weights of factors based on each expert's opinion.

Table 3
Comparisons between Best/Worst Sub-Factors

Expert no.	Best (B) and Worst (W) Sub-Factors		B/W Sub-Factors Compared to Other Sub-CFs. (No. of Sub-CF Shown Below) 1	2	3	4	5	6	8	9	10	12	13	14	15
1	B	SCF2	9	1	8	8	8	8	7	8	8	8	7	8	8
	W	SCF13	3	2	2	3	2	2	2	2	3	2	1	2	2
2	B	SCF3	1	1	1	1	3	2	2	2	3	4	4	3	5
	W	SCF15	7	7	8	7	7	6	5	6	6	6	5	7	1
3	B	SCF5	3	6	4	4	1	6	7	7	7	8	6	6	7
	W	SCF14	4	4	3	4	5	5	4	5	4	5	3	1	3
4	B	SCF10	5	6	5	5	5	3	2	3	1	3	6	7	7
	W	SCF15	6	7	6	6	5	8	8	7	9	5	3	3	1
5	B	SCF1	1	3	4	3	5	7	8	7	8	7	8	9	7
	W	SCF14	8	7	6	7	5	3	2	3	2	3	2	1	4
6	B	SCF5	4	5	8	6	1	6	7	6	8	7	8	8	9
	W	SCF3	5	5	1	5	4	6	6	5	5	6	5	4	6
7	B	SCF2	4	1	5	5	5	4	8	6	7	7	6	4	6
	W	SCF13	6	9	7	7	7	6	3	5	5	5	1	6	4
8	B	SCF1	1	5	6	3	5	5	5	8	6	7	7	7	4
	W	SCF15	6	7	6	8	8	5	6	7	8	8	8	7	1
9	B	SCF3	4	4	1	5	4	5	3	7	7	7	8	7	5
	W	SCF14	6	6	5	6	6	5	5	6	7	6	4	1	4
10	B	SCF2	3	1	2	2	2	3	4	6	6	3	5	5	5
	W	SCF15	8	8	7	8	7	7	7	7	7	8	7	7	1

These weights were then averaged to determine the initial importance of the factors. Figure 3 displays the average weights obtained from the BWM. The top ten CFs with the highest weight values were selected as initially significant and were subsequently used in the next stage for further analysis.

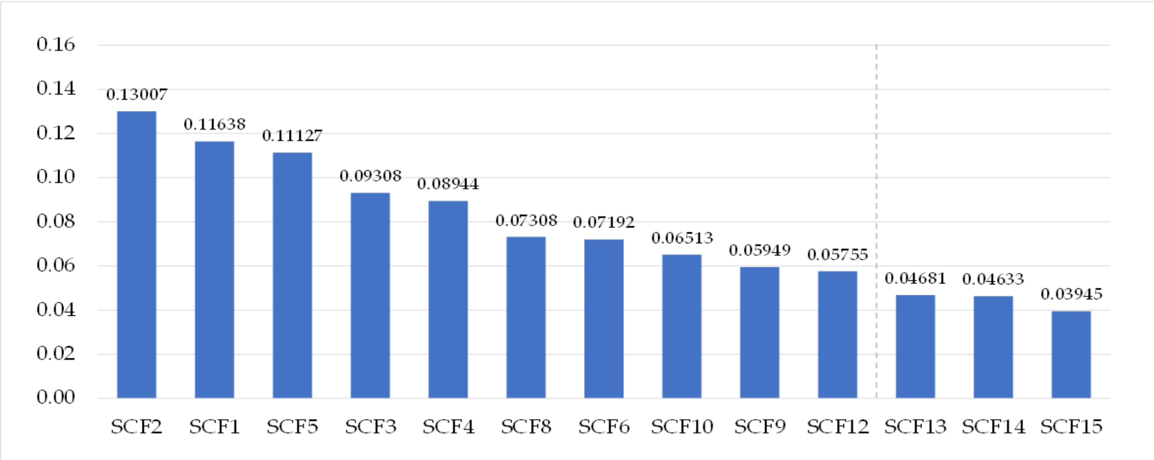

Fig.3. The priorities of CFs obtained from BWM

4.3 DEMATEL-based Technique for Obtaining Relationships between CFs

From the previous stages, two MCF and ten SCF have been selected, as summarized in Table 4. In conjunction with the unique attributes of DEMATEL, a specialist was recruited at this phase to ascertain the correlations among components. We anticipated that the invited expert met the requisite criteria of our study, since he is a senior executive at a premier logistics and warehouse service provider. He possesses more than a decade of direct experience in logistics and the implementation of UAVs in warehouse projects. Initially, the expert discerned the impacts of variables via the organized questionnaire.

Table 4
The Selected CFs and Sub-CFs

Major Factors (Acronym)	Minor Factors (Acronym)
Technology (MCF1)	Hardware (SCF1)
	Software (SCF2)
	Integrated Systems (SCF3)
	Compatibility and Completeness (SCF4)
	User Friendly (SCF5)
Operation (MCF2)	Area or Distance of Operation (SCF6)
	Costs (SCF8)
	Drone Operation (SCF9)
	Warehouse (SCF10)
	Items and Inventories (SCF12)

The findings collected are presented in Table 5-7, which may also display the average matrices. To calculate the initial direct-relation matrix, the greatest value derived from the aggregated values in the last column of each row was utilized to divide all values in the average matrix.

Table 5
The Selected CFs and Sub-CFs

	MCF1	MCF2	Sum
MCF1	0	2	2
MCF2	4	0	4

Table 6
Influences between SCF in Technology Cluster

	SCF1	SCF2	SCF3	SCF4	SCF5	Sum
SCF1	0	4	3	3	3	13
SCF2	4	0	4	4	4	16
SCF3	3	4	0	3	3	13
SCF4	3	4	3	0	3	13
SCF5	3	4	3	3	0	13

Table 7
Influences between SCF in Operation Cluster

	SCF6	**SCF8**	**SCF9**	**SCF10**	**SCF12**	**Sum**
SCF6	0	4	3	4	4	15
SCF8	4	0	2	3	3	12
SCF9	3	2	0	3	2	10
SCF10	3	2	3	0	3	11

The comprehensive relation matrix can be derived using Eq.4 from the original direct-relation matrices and their corresponding identity matrix, as illustrated in Tables 8-10. The threshold values for each matrix were initially computed using the average values of all members within their respective matrices. The decision maker established the threshold values (α). Consequently, the components exhibiting influence levels over the threshold value were incorporated into the NRM, as illustrated in Figure 4.

Table 8
The Total Relation Matrix of MCF

	MCF1	MCF2	$r_i + c_i$	$r_i - c_i$
MCF1	1.0000	1.0000	-1.0000	5.0000
MCF2	2.0000	1.0000	1.0000	5.0000

Note: α = 1

Table 9
The Total Relation Matrix of SCF in Technology Cluster

	SCF1	SCF2	SCF3	SCF4	SCF5	$r_i + c_i$	$r_i - c_i$
SCF1	0.9649	1.3333	1.1228	1.1228	1.1228	0.0000	11.3333
SCF2	1.3333	1.3333	1.3333	1.3333	1.3333	0.0000	13.3333
SCF3	1.1228	1.3333	0.9649	1.1228	1.1228	0.0000	11.3333
SCF4	1.1228	1.3333	1.1228	0.9649	1.1228	0.0000	11.3333
SCF5	1.1228	1.3333	1.1228	1.1228	0.9649	0.0000	11.3333

Note: α = 1

Table 10
The total Relation Matrix of SCF in Operation Cluster

	SCF6	SCF8	SCF9	SCF10	SCF12	$r_i + c_i$	$r_i - c_i$
SCF6	1.0072	1.0455	0.9960	1.1656	1.1103	0.3205	10.3291
SCF8	1.0633	0.7093	0.8218	0.9758	0.9301	0.3561	8.6445
SCF9	0.8799	0.7116	0.5920	0.8471	0.7586	-0.3401	7.9182
SCF10	0.9416	0.7624	0.8092	0.7372	0.8589	-0.6391	8.8580
SCF12	1.1122	0.9155	0.9102	1.0228	0.8056	0.3028	9.2299

Note: α = 1

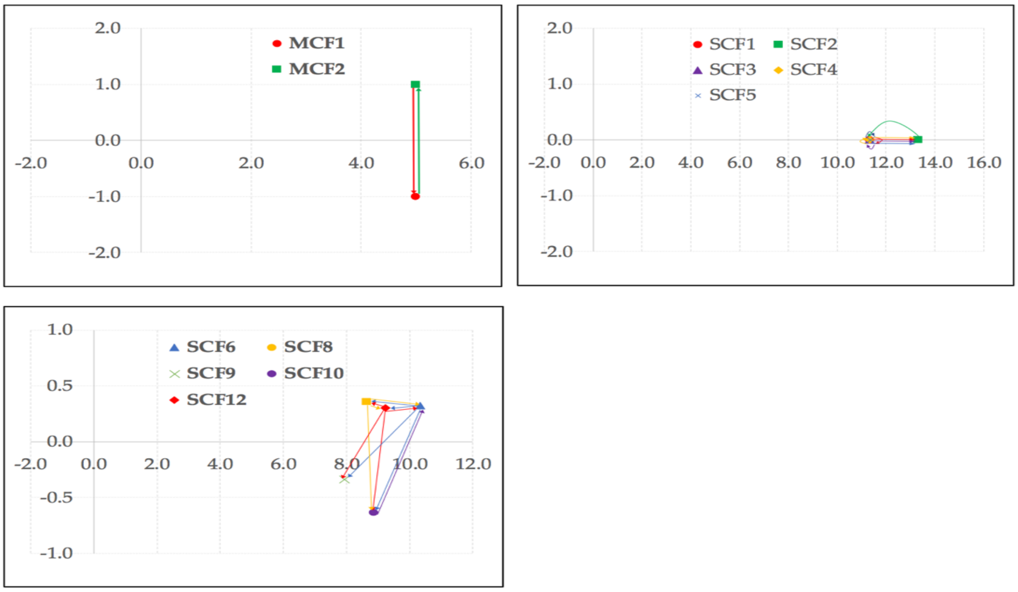

Fig.4. NRM of MCF and their Inner SCF

From the outputs of DEMATEL, the total relation matrix of the MCF level was further normalized. Table 11 represents the outputs provide the weights of relationships among clusters. The influence magnitudes of MCF1 and MCF2 on one another, as indicated in Table 11, are distinct. The DEMATEL method may more accurately reflect the actual weighting identification scenario compared to the conventional ANP approach. The ANP offers a unique benefit at the sub-factor level by accounting for the interrelationships across sub-factors across several categories. Consequently, the ANP was utilized to ascertain the unweighted variables. The ANP outcomes presented in Table 12 were derived from the computation of the unweighted super Matrix.

Table 11
The Transpose of Normalized Total Relation Matrix

	MCF1	MCF2
MCF1	0.33	0.50
MCF2	0.67	0.50

Table 12
The Unweighted Super Matrix

	SCF1	SCF2	SCF3	SCF4	SCF5	SCF6	SCF8	SCF9	SCF10	SCF12
SCF1	0.000	0.517	0.354	0.148	0.119	0.000	0.375	0.127	0.000	0.000
SCF2	0.502	0.000	0.354	0.426	0.460	0.000	0.168	0.377	0.000	1.000
SCF3	0.290	0.226	0.000	0.231	0.201	0.000	0.180	0.194	0.000	0.000
SCF4	0.101	0.124	0.131	0.000	0.220	0.000	0.096	0.121	0.000	0.000
SCF5	0.107	0.134	0.161	0.195	0.000	0.000	0.180	0.181	0.000	0.000
SCF6	0.000	0.180	0.000	0.000	0.000	0.000	0.250	0.333	0.297	0.667
SCF8	0.113	0.100	0.250	1.000	0.250	0.163	0.000	0.000	0.163	0.333
SCF9	0.257	0.353	0.750	0.000	0.750	0.000	0.000	0.000	0.000	0.000
SCF10	0.298	0.168	0.000	0.000	0.000	0.297	0.000	0.000	0.000	0.000
SCF12	0.333	0.199	0.000	0.000	0.000	0.540	0.750	0.667	0.540	0.000

The weights of the clusters and the unweighted super matrix in Table 11-12 were multiplied to derive the weighted super matrix. The global weights of all factors were obtained by calculating the limit super matrix through exponentiation of the weighted super matrix until convergence was

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achieved. The outcomes of the limit super matrix are presented in Table 13.

Table 13
The Weighted Super Matrix

	SCF1	SCF2	SCF3	SCF4	SCF5	SCF6	SCF8	SCF9	SCF10	SCF12
SCF1	0.000	0.083	0.083	0.083	0.083	0.000	0.100	0.100	0.000	0.000
SCF2	0.083	0.000	0.083	0.083	0.083	0.000	0.100	0.100	0.000	0.500
SCF3	0.083	0.083	0.000	0.083	0.083	0.000	0.100	0.100	0.000	0.000
SCF4	0.083	0.083	0.083	0.000	0.083	0.000	0.100	0.100	0.000	0.000
SCF5	0.083	0.083	0.083	0.083	0.000	0.000	0.100	0.100	0.000	0.000
SCF6	0.000	0.133	0.000	0.000	0.000	0.000	0.250	0.250	0.333	0.250
SCF8	0.167	0.133	0.333	0.667	0.333	0.333	0.000	0.000	0.333	0.250
SCF9	0.167	0.133	0.333	0.000	0.333	0.000	0.000	0.000	0.000	0.000
SCF10	0.167	0.133	0.000	0.000	0.000	0.333	0.000	0.000	0.000	0.000
SCF12	0.167	0.133	0.000	0.000	0.000	0.333	0.250	0.250	0.333	0.000

The weights of factors from Table 14 were used to prioritize the ranks of all factors, as shown in Figure 5. According to the results in Figure 5, the top ten CFs were ranked by the weight obtained from our proposed method. The cost factor (SCF8) received the highest weight, followed by the Items and inventories factor (SCF12), Area or distance of operation factor (SCF6), and Software factor (SCF2), each with an importance weight greater than 0.1. The remaining CFs, ranked in descending order, include Warehouse (SCF10), Drone operation (SCF9), Hardware (SCF1), Integrated systems (SCF3), Compatibility and completeness (SCF4), and User-friendly (SCF5).

Table 14
The Limit Super Matrix

	SCF1	SCF2	SCF3	SCF4	SCF5	SCF6	SCF8	SCF9	SCF10	SCF12
SCF1	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
SCF2	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129	0.129
SCF3	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
SCF4	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
SCF5	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
SCF6	0.153	0.153	0.153	0.153	0.153	0.153	0.153	0.153	0.153	0.153
SCF8	0.212	0.212	0.212	0.212	0.212	0.212	0.212	0.212	0.212	0.212
SCF9	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059
SCF10	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
SCF12	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170	0.170

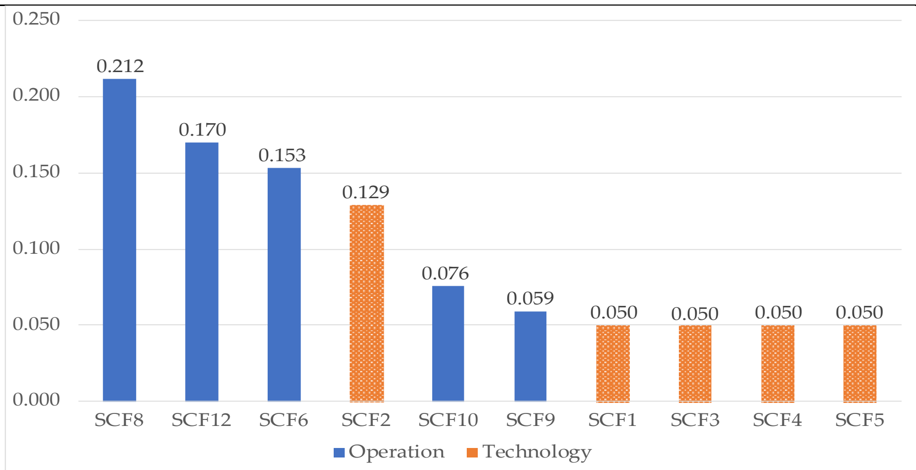

Fig.5. The Final Priorities and Weights of CFs

The focus on the cost factor (SCF8) highlights the importance of financial feasibility in implementing UAVs in warehouses, aligning with the broader goal of business profitability for both organizations and customers. As with other emerging technologies, UAV adoption is primarily driven by its financial viability and the business returns [6]. The impacts of this factor have been discussed in various contexts, such as inventory management costs [20], maintenance costs [13], delivery costs [21], and overall warehouse costs [4]. Past studies consistently emphasize that the success of UAVs in warehouse management is not only based on operational effectiveness but also on the associated costs and financial considerations. The second significant factor is Items and Inventory (SCF12), which directly influences the feasibility and success of UAV adoption. Among these factors, the size, dimensions, and weight of items are crucial, as larger and heavier items increase the likelihood of UAV adoption failure in warehouse operations [18; 27]. Additionally, a large inventory quantity requires companies to invest in larger UAV fleets, impacting financial feasibility [25]. Therefore, companies must carefully assess the suitability of their items and inventory to ensure successful UAV implementation in warehouse management.

It can be observed that operational factors have a greater influence on drone adoption than technological factors. Notably, the top three ranked CFs are all operationally related. This suggests that CFs under MCF2, which are more controllable, are given more focus by researchers and practitioners than those under MCF1. Operational factors are internal criteria that organizations can control, whereas factors like hardware, software, and integrated systems (MCF1) are external and often developed by outside parties. Therefore, the success of UAV adoption largely depends on how well an organization manages its operational factors to maximize profitability. The better the organization optimizes warehouse operations, the greater the returns from adopting UAVs.

5. Conclusion

The use of UAVs in warehouse management offers significant benefits for both organizations and customers, reducing costs and time while enhancing customer satisfaction, operational efficiency, and competitive advantage. However, successful adoption depends on several critical factors. This study aims to identify and prioritize these factors using a hybrid multi-criteria decision-making method that integrates the Delphi technique, BWM, DEMATEL, and ANP, addressing challenges such as inconsistent decision-making and time/resource constraints. Through four stages, the Delphi technique gathered expert opinions on initial factors, BWM filtered the most influential factors, DEMATEL analyzed their interrelationships, and ANP determined their final weights and priorities. The analysis identified ten critical factors, with cost being the most influential, followed by items and inventory, and the area or distance of operation. Cost encompasses financial aspects related to inventory management, maintenance, and delivery, while items and inventory impact UAV flight capacity and often require higher investment. Operational area or distance is also a major consideration. These factors highlight the importance of operational aspects for businesses to consider. In conclusion, the prioritized factors emphasize the need for research and practitioners to focus on these determinants for successful UAV adoption, while businesses must also consider potential barriers. The proposed method addresses inconsistent expert decision-making and enables efficient factor identification, though the study's reliance on expert opinion without empirical validation of interrelationships is a limitation. Future research should include a broader range of experts and industries to empirically validate these relationships through comparative studies. Ultimately, this study contributes to defining the key requirements for UAV adoption in warehouse and SCM, and future research should explore these factors to enhance understanding and implementation strategies.

Author Contributions

Conceptualization, R.W.; methodology, R.W.; software, R.W. and C.M.; validation, R.W., and C.M.; formal analysis, R.W., and C.M.; investigation, C.M.; resources, R.W., and C.M.; data curation, C.M.; writing—original draft preparation, R.W., and C.M.; writing—review and editing, C.M.; visualization, C.M.; supervision, R.W.; project administration, C.M.; funding acquisition, R.W. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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