NEW DECISION MAKING MODEL FOR THE EVALUATION OF KEY CRITICAL SUCCESS FACTORS FOR THE IMPACTS OF DIGITIZATION, ARTIFICIAL INTELLIGENCE (AI), AND CYBER WARFARE ON THE HUMANITARIAN ENVIRONMENT DURING ARMED CONFLICTS

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Abstract: In this article, we have proposed a novel decision making model to investigate the most important and critical success factors (CSFs) affecting the humanitarian environment due to the impacts of digitization, artificial intelligence (AI), and cyber warfare. We have proposed a hybrid decision making model by combining analytical hierarchy process (AHP) with the multi attributive border approximation area comparison (MABAC) technique to evaluate the CSFs of anticipated study. The anticipated hybrid decision making model highlights and measures the effects of different key success factors on humanitarian outcomes, enabling more informed decision-making in the context of evolving digital technologies and security threats. Our projected decision making model offers a broad methodology to deal with complexity of connections among digitalization, artificial intelligence (AI) and cyber warfare on the humanitarian environment ensuring accurate evaluation and strategic planning.

Keywords: Critical success factors (CSFs), Digitalization, Artificial intelligence (AI), Cyber warfare, Analytical Hierarchy Process (AHP), International Humanitarian Law, Multi-criteria decision-making (MCDM).

1. INTRODUCTION

The interconnectivity in current digitally advanced world increasing exponentially. This increase brings new challenges to humanitarian environment. The humanitarian environment across the globe are now facing new and emerging challenges exhibited by digitization, artificial intelligence (AI), and cyber warfare. These digitally advanced technological developments carry equally new beginnings and threats, considerably influence the efficiency of humanitarian efforts. As organizations strive to navigate this complex landscape, identifying and evaluating the critical success factors (CSFs) that influence their operations becomes paramount. Mostly every nation across the globe is endeavor to pilot this complex landscape by recognizing and weighing the key factors that influence their actions becomes dominant.

The traditional decision making techniques is usually fails to address the complex nature of problems arises in engineering and sciences, demanding the improvement and development of appropriate models. This investigation presents a new hybrid mechanism of decision making namely AHP along with MABAC. The AHP is subjective decision making technique which enables a well-organized mechanism
to highlighting CSFs by sub-dividing into sub-criteria, permitting for a stronger understanding of their cross-fertilization.

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The combination of two decision making techniques namely AHP and MABAC devised a widespread mechanism for the evaluation of influences of digitalization, AI, and cyber warfare on humanitarian initiatives under arm conflict. This problem is multifaceted due interconnectivity among various factors which necessitating the demand of robust hybrid decision making model. The anticipated model is twofold, firstly it investigates and identifying the most important CSFs and secondly this mechanism ropes the tactical development and well-versed decision-making in a fast progressing situation.

1.1. Literature Review

The exponential increase in use of digitalization, artificial intelligence and cyber warfare get more attentions in last one decade and its implications over humanitarian efforts. These advanced technologies have transformative effects on several sections across the globe. The effect of these technologies over humanitarian environment are still area of interest for further investigation.

The research and innovation in new direction after advancement in digitalization improve the mostly all aspects of our daily operational works to drive the well informed decision-making within the scope of humanitarian organizations (Khidhir,2024). After the advancement of digitalization also get rise to many challenges such as information confidentiality, secrecy of information, security concerns and cyber warfare. The advancement in these sectors surely affecting the reasonable access to advancement of technologies (Patil & Madaan, 2024).

The chief role of AI in humanitarian energies has been widely recognized with its applications in several newly emerging areas of science and technology where we need automated and well organized decision making for it supply distribution (Crawford & Calo,2016). This investigation also indicates that the use of AI improves the progressions and enrich receptiveness. This may raise ethical distresses concerning partiality and responsibility (O'neil,2017). Accordingly, the investigation and evaluation of key critical success factors linked with AI applications and implementation in humanitarian organizations plays an important role in order to boost the benefits by mitigation the threats.

Everyday world is facing new challenges due to its digitalization. This digitalization ultimately brings new types of challenges under the umbrella of cyber warfare with unique set of encounters for humanitarian environment as a result of disruption of online services and compromise sensitive information. The literature study underlines the essentialness of the robust cybersecurity procedures and tactical development to defense humanitarian edges against these digital terrorizations (Al-Nassiri et al., 2024).

The decision making models play a vital role because of the interdisciplinary nature of complex problems with multi-dimensions and directions. There are several decision making techniques depending upon the information availability and weight allocation. Data can be classified broadly in two categories, namely qualitative and quantitative respectively. The Analytical Hierarchy Process (AHP) is one of the qualitative types of decision making techniques. This technique is broadly used in several fields for ordering and estimating best options based on hierarchical structuring of decision criteria (Saaty,.1980) Similarly, Multi-criteria decision-making (MCDM) techniques, such as the Multi Attributive Border Approximation Area Comparison (MABAC), deal with outlines for measuring choices when confronted with numerous contradictory benchmarks (Wang et al., 2024)

Despite the growing body of literature on these topics, there remains a gap in comprehensive models that integrate AHP and MABAC to evaluate CSFs in the context of digitization, AI, and cyber warfare. This study aims to bridge this gap by presenting a new decision-making model that enhances the understanding and evaluation of these critical factors, ultimately contributing to more effective humanitarian strategies in the face of technological advancements and threats.

1.2. Related Studies

The access of real time digital information enhances decision-making in difficult situation by using data analytics techniques (Khidhir,2024). The utilization of technology in an effective way overcome the socio-economic disparities under the humanitarian contexts as investigated by Patel et., al. (2024). Crawford and Calo (2016) (explore AI and its applications by programmed resource distribution and predictive modelling. They also investigated ethical concerns like model error and liability. There is always a need of cybersecurity measures because of cyber warfare to humanitarian organization as investigated by Shackleford (Partipilo & Stroppa,2023). The integrity against cyberwarfare and its strategic planning was completely studied by Al-Nassiri et at. (2024). The studies on multi-criteria decision-making (MCDM) techniques include Saaty's introduction of the Analytical Hierarchy Process (AHP) for ranking decision measures, and Wang et al. (2024) implemented the MABAC technique for estimating several attributes. Wu et al. examine the combination of AHP with other decision-making structures, emphasizing the latent of a hybrid model to improve feature valuation, which aligns with the existing study's goals (Du et at.,2023). Birkland, Kendra & Wachtendorf underline the significance of tactical formation and structural knowledge to progress flexibility and response efficiency in humanitarian determinations (Dai & Azhar, 2024, Kendra & Wachtendorf, 2003). These connected studies offer a concrete footing for emerging an innovative decision-making model that incorporates AHP and MABAC, highlighting the importance of digitization, AI, and cybersecurity in the humanitarian sector.

1.3. Motivation of This Study

- The motivation of this proposed work is to investigate the challenges that emerges due to interconnection of digitalization, artificial intelligence (AI) and cyber warfare in the humanitarian sector.
- Highlights the need for strong structures that enable well-versed decision-making within fast technological developments.
- Identifies the benefits of digitization and AI in improving functioning efficiency but also recognizes threats associated to cyber warfare, comprising data security apprehensions.
- Underlines the essential for a model that categorizes critical success factors (CSFs) while speaking exposures from evolving intimidations.
- Our intention is to advance out-of-date decision-making procedures by integrating AHP and MABAC for effective approach prioritization and valuation.
- Strengthens the study’s significance to the United Nations Sustainable Development Goals (SDGs), encouraging flexibility and adaptableness in humanitarian determinations.

1.4. Novelty of Proposed Research Work

- Combines Analytical Hierarchy Process (AHP) with Multi Attributive Border Approximation Area Comparison (MABAC) for a robust decision-making framework in humanitarian contexts.
- Addresses the interplay between digitization, AI, and cyber warfare, filling a critical gap in existing literature.
- Offers a holistic model that prioritizes critical success factors (CSFs) while assessing their interdependence.
- Provides a structured tool for humanitarian organizations to evaluate and prioritize strategies in complex technological landscapes.
- Contributes to global initiatives by promoting resilience and sustainability in humanitarian practices.
- Demonstrates the effectiveness of hybrid decision-making approaches, encouraging further exploration in complex decision scenarios.

1.5. Contribution of this Study

This study makes several key contributions to the field of humanitarian decision-making and management:

- Introduces a comprehensive framework combining AHP and MABAC for evaluating critical success factors (CSFs) related to digitization, AI, and cyber warfare.
- Addresses the convergence of advanced technologies and security threats, providing insights into their collective impact on humanitarian efforts.
- Offers a practical tool for organizations to make informed decisions, enhancing resilience and adaptability in a rapidly changing environment.
- Expands the application of multi-criteria decision-making techniques, contributing valuable references for future research and practical applications.
- Inform policymakers and practitioners on best practices for technology adoption and risk management in the humanitarian sector.
- Aligns with global initiatives, helping organizations position themselves to achieve relevant UN Sustainable Development Goals (SDGs).

2. MULTI CRITERIA DECISION MAKING

Multi criteria decision making MCDM is a term used for defining multiple methods which are used to implement for making decision about selecting the most appropriate option among the number of listed options based on multiple conflicting criteria. It contains several objective and subjective methods for evaluating and obtaining weights of criteria. For quantitative data, the objective ranking method is used to apply while for qualitative type of data, different subjective approaches can be implemented. Here in this research study, we opted one of the MCDM subjective approaches known as Analytical hierarchy process (AHP) for obtaining weights of criteria and through three different decision makers we obtain pairwise comparison matrix and then on those matrices we implement an objective MCDM distance based approach called as Multi attributive border approximation method for the ranking and selection of optimal criteria.

2.1 Analytical Hierarchy Process

In 1998, an American mathematician Thomas L. Saaty introduced a subjective type of decision making framework known as Analytical hierarchy process (AHP) for the solution of the complex problems that can arise in different fields of interest where the decision making is involved. Implementation of AHP on any simple as well as complex problem involves several pairwise comparisons of the options or criteria which are considered for evaluation. Decision makers are responsible for making pairwise comparison matrix based on their experience, ground realities and best judgement (Saaty,2008).

They compare criteria with each other as how each criterion having significant importance upon other criterion by using an ordinal scale (1- 9) defined by Saaty et al. (2008) as shown in figure 2. This scale is opted to support in obtaining the importance level of each criterion or option against the rest ones (Franek & Kresta,2014). In order to make a reliable judgement with given criteria, more than one decision maker can also make pairwise judgements and pairwise comparison matrix to achieve the desired goal. The working flowchart of AHP is shown in Figure 1.

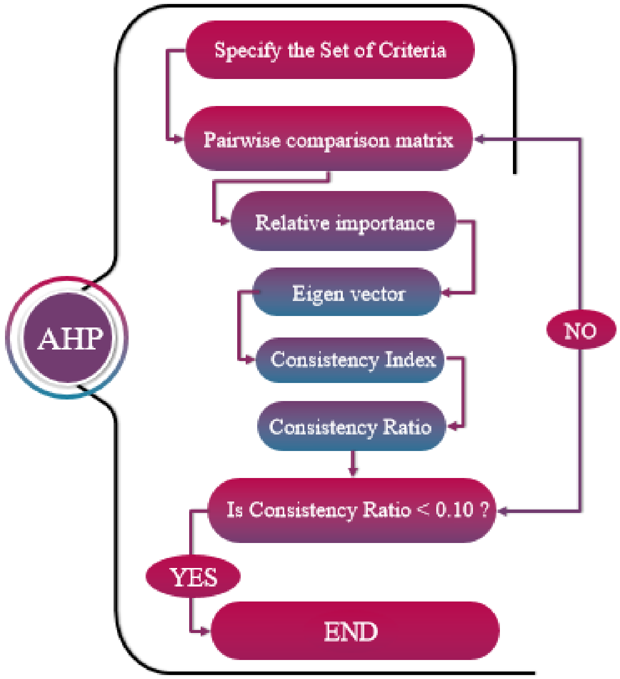

Figure 1: Working process of Analytical Hierarchy Process

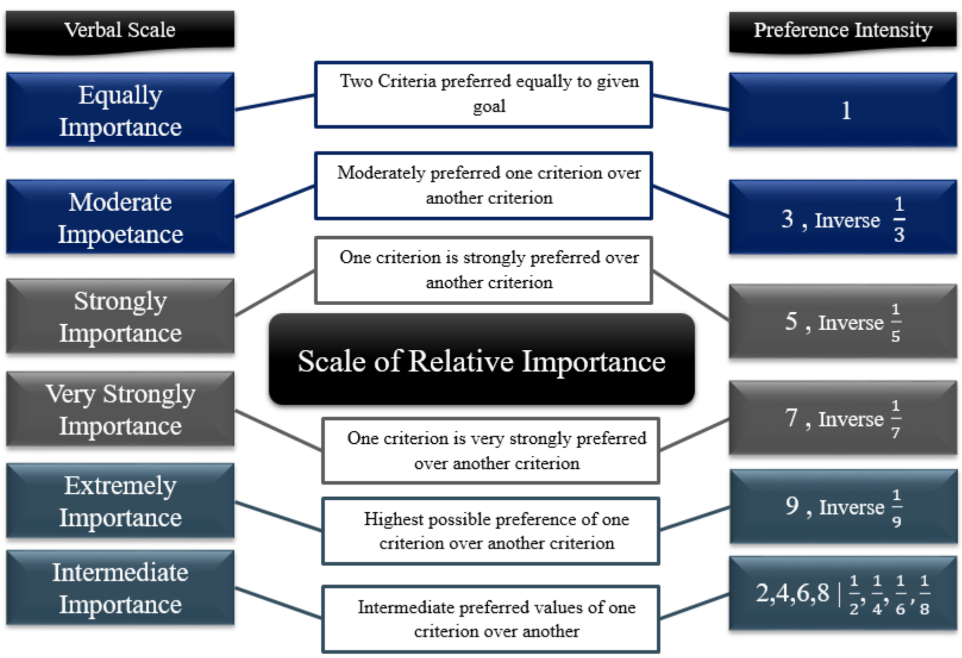

Figure 2: Saaty`s scale of relative importance of activities

AHP is six steps based MCDM method used for determining weighted vector of each criterion on the basis of one or more than one pairwise comparison matrices. These steps are defined below.

Step I: To begin with, we have to set the goal and specify the number of criteria on which we are going to make decisions to reach our desired goal.

Step II: In second step, we have to design a pairwise comparison matrix which is fundamental and crucial in AHP. The pairwise comparison matrix consist of comparisons of two activities on a scale of 1-9 which was defined by T.L Saaty given in Figure 2. Each criterion is compared with all other criteria based on this scale. The level of importance is set by the decision makers based on their experience, judgements and knowledge regarding the case study. Every component of the pairwise comparison matrix *P* is denoted with P_{ij} which will be compared with the i^{th} Component with all j^{th} terms of level of preferences from equal to extremely importance preference (Zardari et al.,2014):

$$P = \begin{bmatrix} c_{11} & c_{12} \dots & c_{1j} \\ c_{21} & c_{22} \dots & c_{2j} \\ \vdots & \vdots & \vdots \\ c_{i1} & c_{i2} & c_{mn} \end{bmatrix}, \tag{1}$$

where $[c_{ij}]$ represents pairwise comparison matrix and $i \leq i \leq m, 1 \leq j \leq n$. The value of this matrix belongs to Saaty`s scale table. Also, the diagonal entry of this matrix is 1 means the comparison of an activity or criterion with itself is equal to 1. The comparison between the activities can be calculated as:

$$c = \frac{n(n-1)}{2} \tag{2}$$

where *n* in the number of activities that are under consideration.

Step III: Now we have to normalize the pairwise comparison matrix by summing up each all entries of each column and then divide each column entry by that sum value as:

$$\bar{\eta}_{ij} = \frac{c_{ij}}{\sum_{k=1}^{n} c_{kj}}, \tag{3}$$

After normalization of pairwise comparison matrix, we again sum the column of the this generated normalized matrix as:

$$\delta_i = \sum_{j=1}^{n} \bar{\eta}_{ij}, \qquad i = 1,2,3,\dots n \tag{4}$$

Then our desired result in this study is now calculated which is the weight of each criterion by using the given formula;

$$weight \ = \ w_i = \frac{\delta_i}{\sum_{i=1}^{n} \delta_i}, \tag{5}$$

The Eq. (5) gives the weighted vector of each criterion based on their relative importance.

Step IV: In previous step, the weights of criteria can be calculated by implementing all parts of third step. After calculating weight, we now have to find the eigenvector (weighted sum vector) to calculate the λ, which is used to check the consistency ratio. We again calculate the weighted normalized matrix as multiplying weights of each criterion with its column of pairwise comparison matrix and then the weighted sum vector. The expression for weighted sum is given as follows:

$$\varpi_n = w_i P_{ij}. \tag{6}$$

Weighted sum vector

$$\varpi_{\delta} = \frac{\sum_{j=1}^{m} \varpi_{n_j}}{w_j}\ , \tag{7}$$

where $i = 1,2,3,\ldots n$ and $j = 1,2,3,\ldots m$ and. For calculating λ we obtain the average value of the weighted sum vector:

$$\lambda = \frac{\sum_{j=1}^{m} \varpi_{\delta_j}}{n}, \tag{8}$$

where *n* is the number of criteria or activities that are under consideration.

Step V: After calculating λ, we now find the consistency index *CI* and random index *RI* for finding the consistency ratio. If n is the O is the order of pairwise comparison matrix, then we can find *CI* by the formula:

$$CI = \frac{\lambda - O}{O - 1}, \tag{9}$$

Now the random index (RI) can be easily calculated by using the table given in (Saaty,2008). The random values for up to 10 variables, criteria or activities are given in Figure 3.

Matrix Size Order n	$n=1$	$n=2$	$n=3$	$n=4$	$n=5$
RI values	0.00	0.00	0.58	0.90	0.12

Random index table by T.L Saaty

Matrix Size Order n	$n=6$	$n=7$	$n=8$	$n=9$	$n=10$
RI values	1.24	1.32	1.41	1.45	1.49

Figure 3: Random indices table for up to order 10 matrix

Step 6: In the final step of AHP, we calculate the consistency ratio (CR) which is crucial part in this method. This ratio is calculated for checking the acceptability of pairwise comparison of criteria by the experts. The expression for finding the CR value is given below:

$$CR = \frac{CI}{RI}. \tag{10}$$

The lower than 0.10 CR value shows the decided comparison steps taken great and the matrix values are acceptable but if the value of CR is higher than 0.10 then revision of comparisons using values from figure 3 is crucial to maintain the decision matrix consistent.

An analytical hierarchy process used by several decision makers both by individual and by group decision making such as Lie et al. (Zardari et al.,2014) used this subjective method for evaluation of multimedia authorizing system with group decision. For the selection of best contractor in project management, Al Harbi implemented this method (Vaidya & Kumar, 2006). For the selection of optimal casting suppliers from an evaluated group of suppliers, Akarte et al. applied this method on problem. AHP was used in educational, social, political, manufacturing industry, engineering and for personal interests. However, with its usage in decision making, a lot of criticism has also been launched over the years that this method is time-taking, not consistent as it depends on personal judgement, which may be wrong sometimes and the comparison process may take longer than ever if the number of activities increases. In that case it's difficult to manage the accuracy in evaluation of criteria over each other (Vaidya & Kumar, 2006).

2.2 Multi Attributive Border Approximation Area Comparison

There are multiple methods in MCDM which are distance based methods such as TOPSIS, EDAS, CODAS etc. Multi Attributive Border Approximation Area Comparison (MABAC) is also one of the newly introduced distances based methods used to solve the complex kind of problems in which the making a decision is needed (Wei et al.,2019). MABAC is one of the objective decisions making methods which provides a suitable way for evaluation and comparison of different alternatives on the basis of critical defined criteria. It was introduced by Pamucar and Cirovic (2015) for the selection of transport and handling and resources. This method derives the measure of distance between every possible alternative and bored approximation area. It facilitates more informed and balanced decision making. After obtaining the criteria weights, we now can apply the MABAC decision making method (Delice, A. P. E. K. (2017).

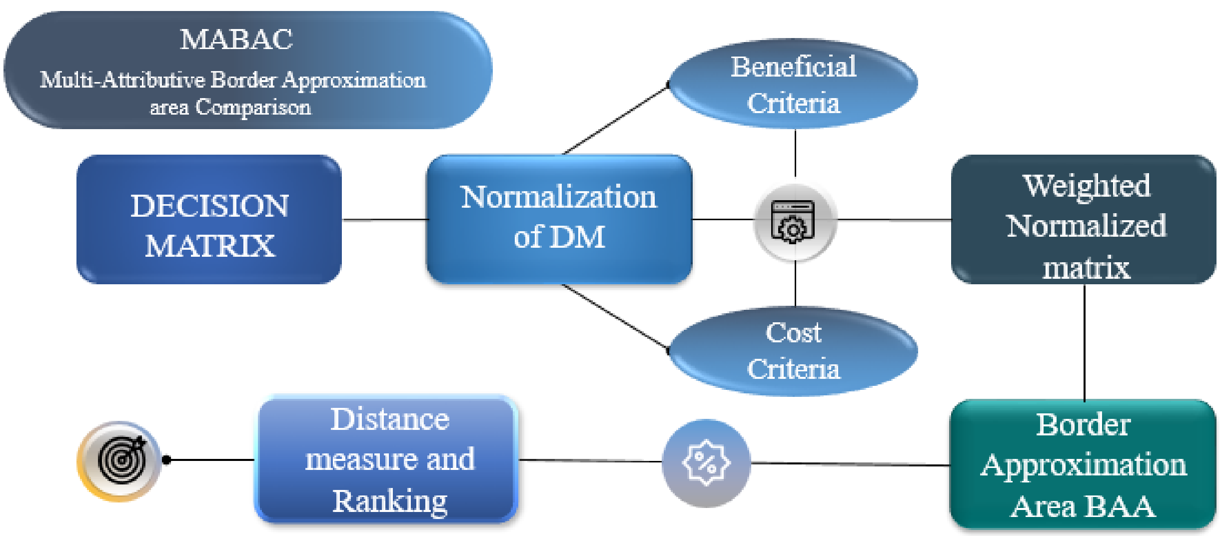

Figure 4: Flow chart of MABAC method

The mathematical steps of Multi Attributive Border Approximation Area Comparison (MABAC) method is listed below

Step I: Formulation of initial decision matrix is needed to proceed with this method. The decision matrix and decided by the decision makers based on their experience and judgements. The matrix which contain the number of option regarding their criteria is known as the decision matrix represented here by ψ where the options are represented by $A_i = (\psi_{i1}, \psi_{i2}, \dots, \psi_{in})$ can be formulate as;

$$\psi = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} \psi_{11} & \psi_{12} \cdots & \psi_{1n} \\ \psi_{21} & \psi_{22} \cdots & \psi_{2n} \\ \vdots & \vdots & \vdots \\ \psi_{m1} & \psi_{m2} & \psi_{mn} \end{bmatrix} \quad (11)$$

where *m* represents the number of options being evaluated and *n* illustrates their corresponding criteria.

Step II: After setting the decision matrix one to have the unit less than the decision matrix which is called normalization. It can be implemented on both benefit and cost elements of alternatives separating by two different mathematical expressions which are listed below.

For favorable criteria we use this expression for normalization of values given in decision matrix;

$$\eta_{ij} = \frac{\psi_{ij} - \min \psi_i}{max\ (\psi_{\mathrm{i}}) - \min(\psi_{i)}}, \tag{12}$$

And the formula for cost criteria which is not favorable for our desired outcomes is given;

$$\eta_{ij} = \frac{\psi_{ij} - \max \psi_i}{min\ (\psi_{\mathrm{i}}) - \max \psi_i}. \tag{13}$$

where the $\max \psi_i$ is the maximum value among all values from $\psi_1\ to\ \psi_m$ and $\min \psi_{\ i}$ is the one lowest value among the values from $\psi_{1\ to}\ \psi_{\ m}$). After calculating the normalized decision matrix we have to calculate the weighted matrix elements by using the expression:

$$\omega_{ij} = \omega_j \ . \ (\eta_{ij} + 1), \tag{14}$$

where ω_j are the calculated weights and η_{ij} represents the normalized values of decision matrix.

Step III: In third step the border approximation area BAA is calculated, and it is the fundamental part of the MABAC method. To obtain its value the following mathematical expression is applied.

$$g_i = \left[\prod_{j=1}^{m} \omega_{ij}\right]^{1/m}. \tag{15}$$

After Obtaining the value g_i for each conflicting element in the decision matrix, A matrix G will be formed which is matrix of a border approximation area with $n\times 1$ order where n represent the number of criteria.

$$G_i = [\ g_1, g_2, \ldots, g_i] \tag{16}$$

G_i matrix is also divided in upper approximation area G^+ consist of favorable alternatives and lower approximation area G^- consist of non-favorable alternatives.

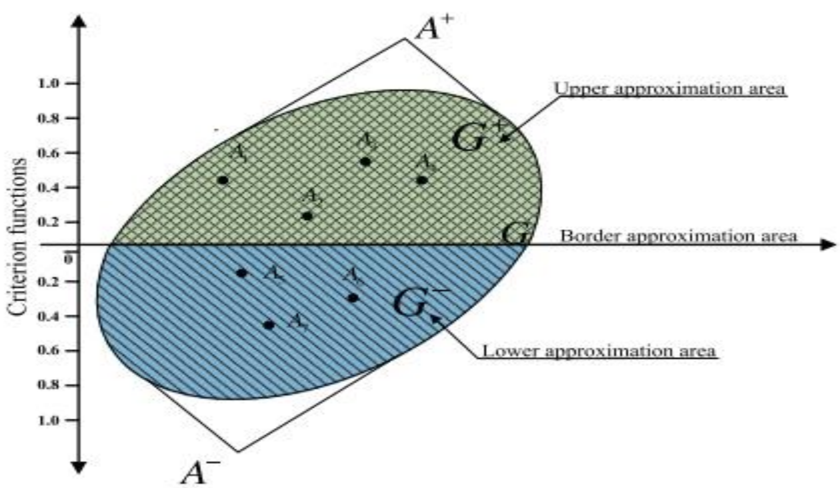

Figure. 5: Presentation of G, G^+ and G^- areas (Pamučar & Ćirović, 2015)

Step IV: This step presents the measure of distance that calculates the performance of each alternative from the border approximation area for every criterion.

$$Q = \omega_{ij} - G_i \tag{17}$$

This measure shows how much an alternative close or far from the ideal performance in each criterion.

Step V: The final step in MABAC method is to rank the alternatives based on the criteria that considered by the decision makers. By the sum of the elements of matrix Q_{ij} by rows we obtain the final values.

$$R_i = \sum_{j=1}^{n} q_{ij} \tag{18}$$

The alternatives are ranked based on scores, with the alternative having the smallest distance (or highest score) being estimated the most preferable.

2.3 Rank Position Method (RPM)

The Rank position method, also known as reciprocal rank method, is often used to synthesize the ranking results derived by different methods. It considers the current position of each option with respect to single method (Altuntas et al.,2015) (Kumar & Kaur, 2024). the mathematical expression of RPM is;

$$RPM = \frac{1}{\frac{1}{rank(method1)}+\frac{1}{rank(method2)}+\frac{1}{rank(method3)}} \tag{19}$$

3. CASE STUDY

In this section of research study, we derive some numerical results for prioritizing the Key Critical Success Factor for impacts of digitization, AI, and Cyber Warfare on humanitarian environment during armed conflicts. These key critical success factors are of a lot of types, but we select only ten for our study. These are Data Security and privacy (DSP), Ethical AI implementation (EAI), Infrastructure Resilience (IR), Cross Sector Collaboration (CSC), Capacity Building and Training (CBT), Legal and Regulatory Compliance (LRC), Adaptive and Scalable Solutions (ASS), Community Engagement and Trust (CET), Monitoring and Evaluation (ME) and Sustainable Funding and Resources (SFR). These all factors are our criteria on which we make results by applying the AHP and MABAC methods. These Criteria are given in Figure 5 with Abbreviations that we use in tables instead of full forms. As in AHP the pairwise comparison matrix is crucial, and it is based on the relative importance values given in Figure 2. In this paper, three pairwise comparison matrices, each formulated by different decision makers, are used in order to enhance the accuracy of our desired outcome. The Analytical Hierarchy Process along with multi attributive border approximation area method implemented on each matrix individually, producing slightly different results.

AHP method was implemented for obtaining the weights of the criteria while the MABAC MCDM method was applied for the ranking and selection of the optimal key critical success factor among the nine other factors. To Synthesize these varying results in a more enhanced single outcome, the rank position method subsequently applied to the values derived from each matrix. The overall research study flowchart is given in Figure 7.

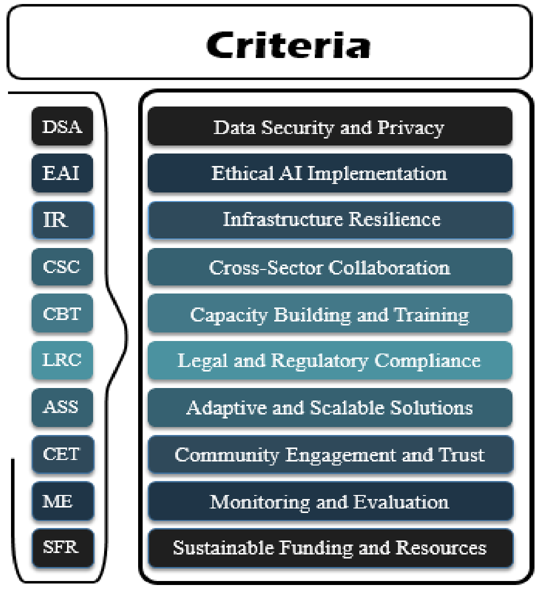

Figure 6: Key critical success factors

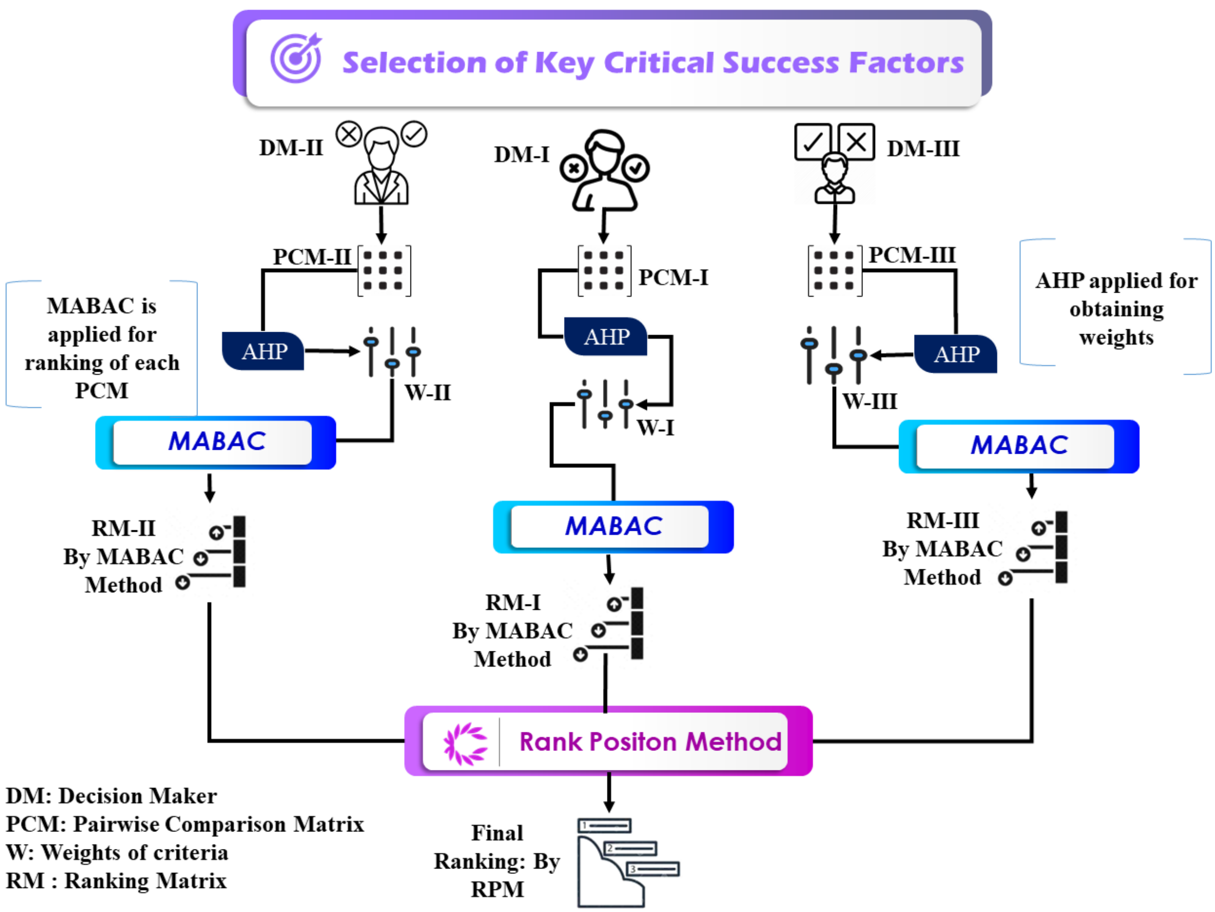

Figure 7: Flowchart of overall process of the research study.

3.1 First Pairwise Comparison Matrix

The first pairwise comparison matrix established by the first decision maker in which he compared each criterion with all criteria on Saaty`s scale of relative preferences values that are from 1 to 9 given in Figure 2. These comparisons of all key critical success factors based on his experience and judgements. After assigning comparison values we applied AHP method to obtain the weights of all ten criteria which are given in Table 2.

Table 1: Pairwise comparison matrix by decision maker-I

Criteria	DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
DSP	1	3	2	3	3	3	3	3	3	4
EAI	1/3	1	1/3	1/3	1/3	1/3	0.5	3	3	2
IR	0.5	3	1	2	0.5	2	2	3	2	3
CSC	1/3	3	0.5	1	2	4	3	3	3	3
CBT	1/3	3	2	0.5	1	3	3	3	2	3
LRC	1/3	3	0.5	0.25	1/3	1	3	3	3	3
ASS	1/3	2	0.5	1/3	1/3	1/3	1	1	1	3
CET	1/3	1/3	1/3	1/3	1/3	1/3	1	1	2	2
ME	1/3	1/3	0.5	1/3	0.5	1/3	1	0.5	1	3
SFR	0.25	0.5	1/3	1/3	1/3	1/3	1/3	0.5	1/3	1

Table 2: Weights of the criteria based on first pairwise comparison matrix -I

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.21653	0.06688	0.13001	0.14927	0.1388	0.10067	0.06133	0.05176	0.05217	0.03257

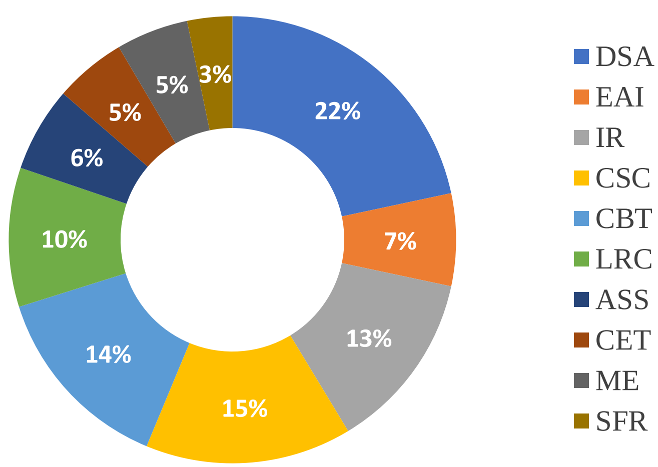

Figure 8: Weights of criteria obtained by AHP method

After getting the matrix which is actually our pairwise comparison matrix, we now apply MABAC method to select the best key factor among the number of factor by using the weights that we calculated by AHP method.

3.2 Applying MABAC Method

Now on provided data we apply MABAC method in which we first need a decision matrix and weights of the criteria. Our decision matrix is given in Table 1 which is our pairwise comparison matrix derived by using the Saaty`s scale values by decision maker-I. after establishing the decision matrix, the second thing in MABAC method is to normalize the decision matrix and then get the weighted matrix. The weighted decision matrix is given in Table 3. Along with normalized decision matrix the G values of each criterion are also given in Table 4.

Table 3: weighted Normalized Pairwise decision matrix-I

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.43306	0.13376	0.26002	0.29854	0.27760	0.17391	0.12266	0.10352	0.10434	0.06514
0.23963	0.08366	0.13001	0.15361	0.13880	0.10067	0.06523	0.10352	0.10434	0.04343
0.28871	0.13376	0.18217	0.24426	0.14764	0.14648	0.09969	0.10352	0.08480	0.05428
0.23963	0.13376	0.14324	0.18998	0.22561	0.20134	0.12266	0.10352	0.10434	0.05428
0.23963	0.13376	0.26002	0.16284	0.17363	0.17391	0.12266	0.10352	0.08480	0.05428
0.23963	0.13376	0.14324	0.14927	0.13880	0.11905	0.12266	0.10352	0.10434	0.05428
0.23963	0.10871	0.14324	0.15361	0.13880	0.10067	0.07672	0.06211	0.06526	0.05428
0.23963	0.06688	0.13001	0.15361	0.13880	0.10067	0.07672	0.06211	0.08480	0.04343
0.23963	0.06688	0.14324	0.15361	0.14764	0.10067	0.07672	0.05176	0.06526	0.05428
0.21653	0.07114	0.13001	0.15361	0.13880	0.10067	0.06133	0.05176	0.05217	0.03257

Table 4: Border approximation area (BAA) matrix

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.25641	0.10217	0.16057	0.17617	0.16169	0.12707	0.09142	0.08137	0.08329	0.05024

After calculating the BAA matrix, we calculate the distance of each criteria performance from the border approximation area matrix. These distances are given in Table 5. The final step of MABAC method is to find the Q-value and then ranking the activities. Table 6 illustrates the value of each criterion along with their ranking.

Table 5: Distance of each criteria performance from the border approximation area matrix

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.17665	0.03159	0.09945	0.12237	0.11591	0.04684	0.03124	0.02215	0.02105	0.01490
-0.01678	-0.01851	-0.03056	-0.02256	-0.02289	-0.02640	-0.02618	0.02215	0.02105	-0.00681
0.03230	0.03159	0.02160	0.06809	-0.01405	0.01940	0.00827	0.02215	0.00151	0.00405
-0.01678	0.03159	-0.01733	0.01381	0.06393	0.07427	0.03124	0.02215	0.02105	0.00405
-0.01678	0.03159	0.09945	-0.01333	0.01194	0.04684	0.03124	0.02215	0.00151	0.00405
-0.01678	0.03159	-0.01733	-0.02690	-0.02289	-0.00803	0.03124	0.02215	0.02105	0.00405
-0.01678	0.00654	-0.01733	-0.02256	-0.02289	-0.02640	-0.01470	-0.01926	-0.01802	0.00405
-0.01678	-0.03529	-0.03056	-0.02256	-0.02289	-0.02640	-0.01470	-0.01926	0.00151	-0.00681
-0.01678	-0.03529	-0.01733	-0.02256	-0.01405	-0.02640	-0.01470	-0.02961	-0.01802	0.00405
-0.03988	-0.03103	-0.03056	-0.02256	-0.02289	-0.02640	-0.03009	-0.02961	-0.03112	-0.01767

Table 6: Final Q-Values Matrix with ranking

Criteria	Q values	Ranking
DSP	0.682160	1
EAI	-0.127487	6
IR	0.194917	4
CSC	0.227980	2
CBT	0.218660	3
LRC	0.018163	5
ASS	-0.147348	7
CET	-0.193732	9
ME	-0.190694	8
SFR	-0.281799	10

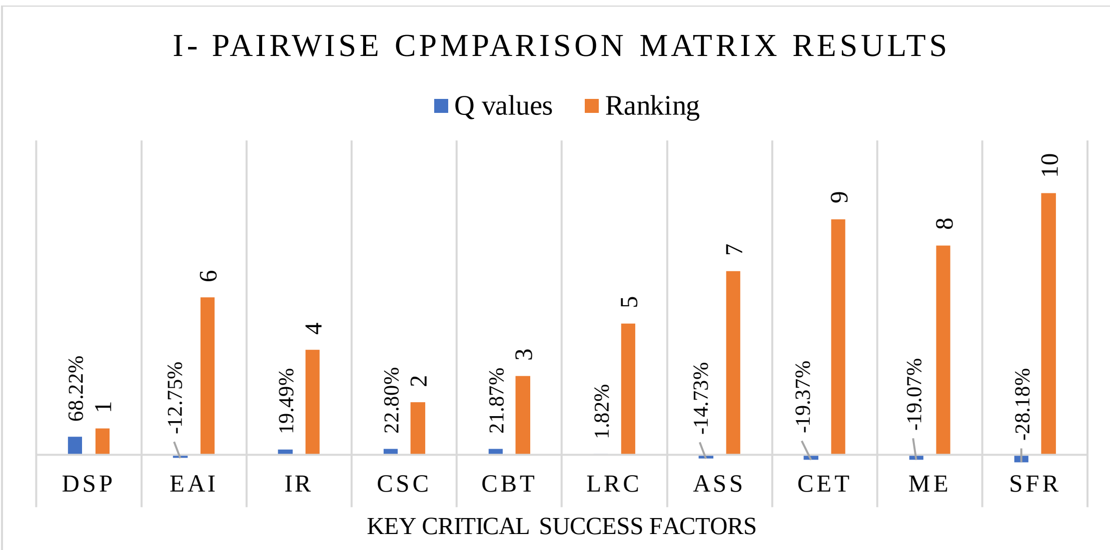

Figure 9: First pairwise comparison matrix results.

3.3 Second pairwise comparison matrix

The second decision maker established the comparisons of all key factors on his judgements and field experience. He also uses the saaty`s scale of relative importance. The second pairwise comparison matrix is given in Table 7. The weights on basis of this comparison table are derived by using AHP method. These obtained weights of criteria are slightly different for some of the activities as changing the comparison values by the second decision maker. The weights given in table 8. After finding weights we applied the MABAC method formulas to get the weighted normalized pairwise decision matrix that is given in Table 9. Table 10 illustrates the border approximation area values and Table 11 shows the distance of each option from the border approximation area values. At the end the Q-values of each option along with ranking is given.

Table 7: Second pairwise comparison matrix by decision maker-II

Criteria	DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
DSP	1	5	5	0.5	4	3	3	5	5	3
EAI	0.2	1	0.5	0.5	1	2	0.5	3	3	2
IR	0.2	2	1	1/3	0.25	2	3	3	4	3
CSC	2	2	3	1	2	2	5	4	5	6
CBT	0.25	1	4	0.5	1	5	3	3	3	4
LRC	1/3	0.5	0.5	0.5	0.2	1	3	3	4	3
ASS	1/3	2	1/3	0.2	1/3	1/3	1	2	3	3
CET	0.2	1/3	1/3	0.25	1/3	1/3	0.5	1	2	2
ME	0.2	1/3	0.25	0.2	1/3	0.25	1/3	0.5	1	3
SFR	1/3	0.5	1/3	1/6	0.25	1/3	1/3	0.5	1/3	1

Table 8: Weights of the criteria of decision matrix-II with AHP method

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.220164	0.079822	0.097512	0.207842	0.141603	0.083993	0.065705	0.039733	0.034658	0.028967

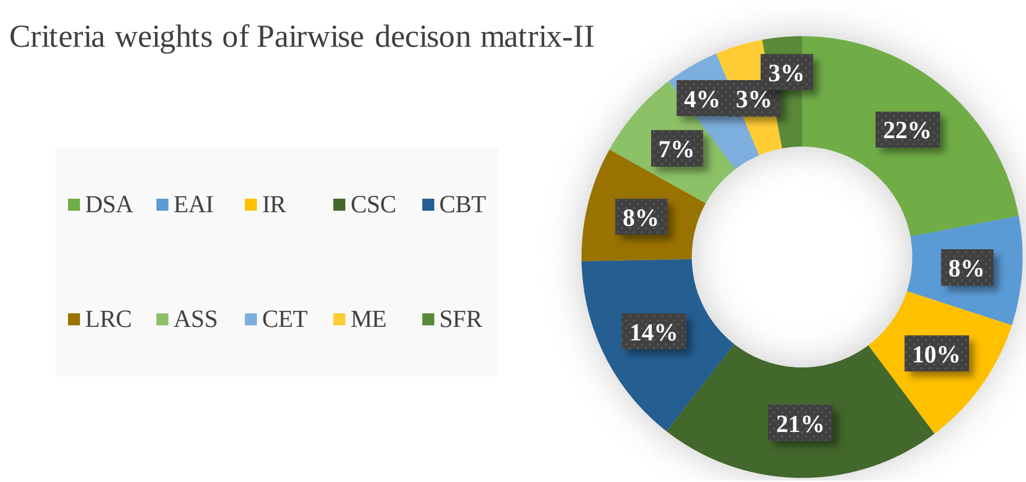

Figure 10: weights of criteria obtained by AHP method.

Table 9: Weighted Normalized decision matrix-II

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.31802	0.15964	0.19502	0.29048	0.28321	0.13262	0.10327	0.07947	0.06932	0.04055
0.22016	0.09127	0.10264	0.29048	0.17141	0.11494	0.06810	0.06181	0.05447	0.03476
0.22016	0.10837	0.11291	0.24791	0.14347	0.11494	0.10327	0.06181	0.06190	0.04055
0.44033	0.10837	0.15397	0.41568	0.20868	0.11494	0.13141	0.07064	0.06932	0.05793
0.22628	0.09127	0.17450	0.29048	0.17141	0.16799	0.10327	0.06181	0.05447	0.04635
0.23607	0.08273	0.10264	0.29048	0.14160	0.09726	0.10327	0.06181	0.06190	0.04055
0.23607	0.10837	0.09915	0.21535	0.14645	0.08541	0.07513	0.05298	0.05447	0.04055
0.22016	0.07982	0.09915	0.22788	0.14645	0.08541	0.06810	0.04415	0.04705	0.03476
0.22016	0.07982	0.09751	0.21535	0.14645	0.08399	0.06570	0.03973	0.03963	0.04055
0.23607	0.08273	0.09915	0.20784	0.14347	0.08541	0.06570	0.03973	0.03466	0.02897

Table 10: Border approximation area matrix values

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.250666	0.097008	0.119473	0.263466	0.166007	0.105583	0.086135	0.055984	0.053505	0.039932

Table 11: Distance values from the border approximation area matrix

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.06735	0.06264	0.07555	0.02701	0.11720	0.02704	0.01714	0.02348	0.01581	0.00062
-0.03050	-0.00573	-0.01683	0.02701	0.00541	0.00936	-0.01804	0.00582	0.00097	-0.00517
-0.03050	0.01136	-0.00656	-0.01556	-0.02254	0.00936	0.01714	0.00582	0.00839	0.00062
0.18966	0.01136	0.03449	0.15222	0.04267	0.00936	0.04527	0.01465	0.01581	0.01800
-0.02439	-0.00573	0.05502	0.02701	0.00541	0.06240	0.01714	0.00582	0.00097	0.00642
-0.01460	-0.01428	-0.01683	0.02701	-0.02440	-0.00833	0.01714	0.00582	0.00839	0.00062
-0.01460	0.01136	-0.02032	-0.04811	-0.01956	-0.02017	-0.01100	-0.00301	0.00097	0.00062
-0.03050	-0.01719	-0.02032	-0.03559	-0.01956	-0.02017	-0.01804	-0.01184	-0.00645	-0.00517
-0.03050	-0.01719	-0.02196	-0.04811	-0.01956	-0.02159	-0.02043	-0.01625	-0.01387	0.00062
-0.01460	-0.01428	-0.02032	-0.05562	-0.02254	-0.02017	-0.02043	-0.01625	-0.01885	-0.01096

Table 12: Final Q-Values matrix with ranking

Criteria	Q values	Ranking
DSP	0.43383496	2
EAI	-0.02770934	6
IR	-0.02248172	5
CSC	0.533499036	1
CBT	0.150066721	3
LRC	-0.01945994	4
ASS	-0.12382825	7
CET	-0.18483201	8
ME	-0.20884418	9
SFR	-0.21403358	10

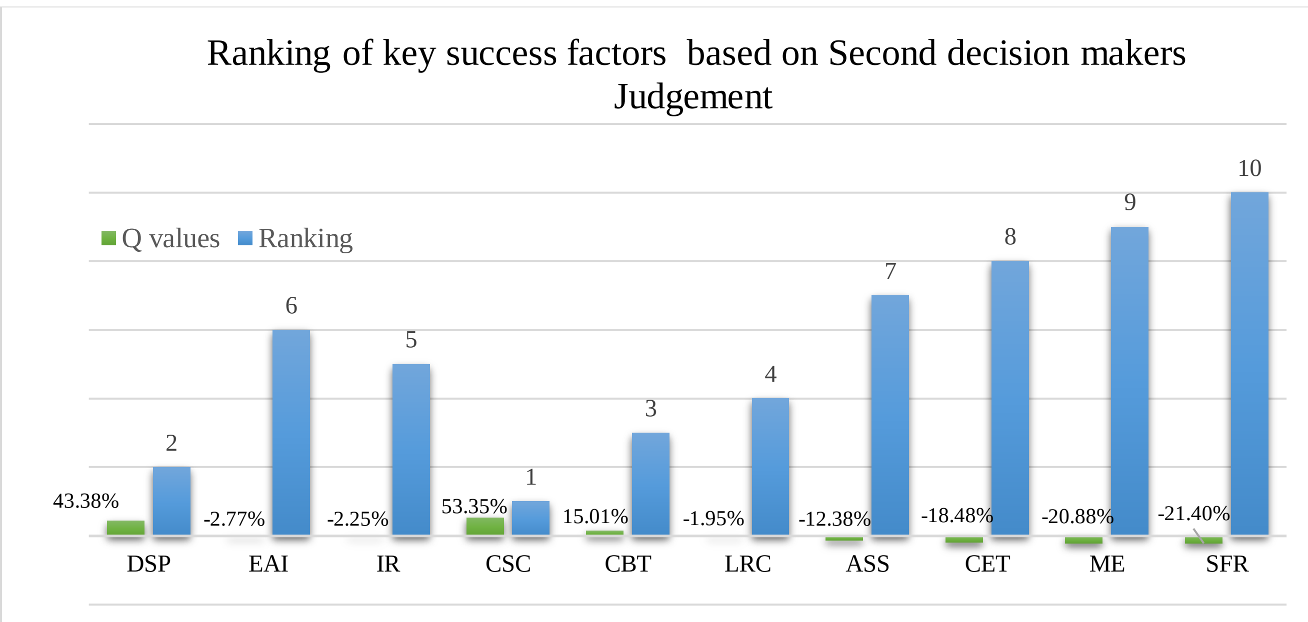

Figure 11: Second pairwise comparison matrix result.

3.4 Third Pairwise comparison matrix

The last decision matrix formulated by the third decision maker is given in table 13 along with the weights of each criterion obtained by AHP method. These comparisons are different than the first and the second decision matrix. These are also based on relative importance scale.

After establishing weights, the weighted matrix element is given in table 14 along with the border approximation area vector of all criteria. Then in Table 15 the distance of each criterion is calculated from the border approximation table. And finally, the final Q-value of each criterion which shows the preferences along with ranking is given.

Table 13: Second pairwise comparison matrix by decision maker-II

Criteria	DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
DSP	1	3	3	3	5	4	4	4	5	3
EAI	1/3	1	0.5	1/3	0.25	1/3	0.5	3	3	3
IR	1/3	2	1	1/3	1/3	3	3	4	3	4
CSC	1/3	3	3	1	2	3	5	4	5	6
CBT	0.2	4	3	0.5	1	3	4	5	4	3
LRC	0.25	3	1/3	1/3	1/3	1	0.5	3	1	3
ASS	0.25	2	1/3	0.2	0.25	2	1	3	2	3
CET	0.25	1/3	0.25	0.25	0.2	1/3	1/3	1	2	0.5
ME	0.2	1/3	1/3	0.2	0.25	1	0.5	0.5	1	3
SFR	1/3	1/3	0.25	1/6	1/3	1/3	1/3	2	1/3	1
Weights	0.25305	0.06298	0.10789	0.18193	0.14960	0.06667	0.07042	0.03325	0.03978	0.03442

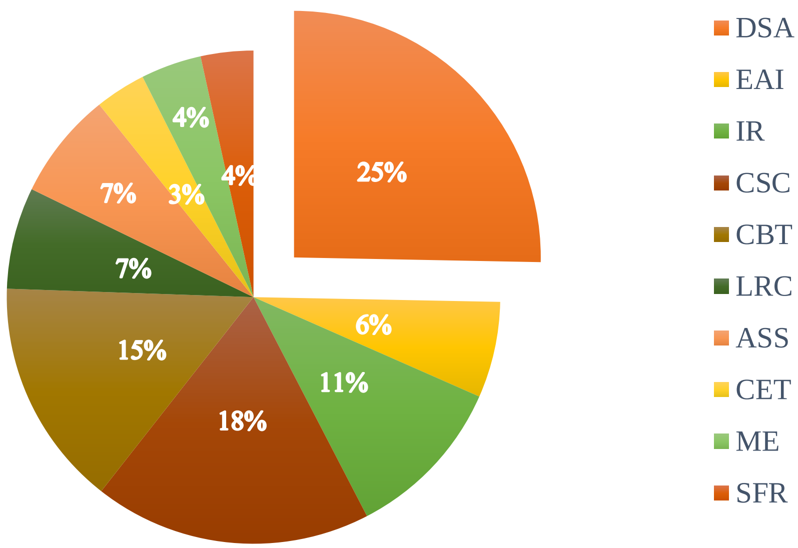

Figure 12: Weights of criteria obtained by AHP method.

Table 14: Weighted normalized decision matrix with MABAC values

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.50610	0.10880	0.21577	0.36386	0.29921	0.13334	0.12576	0.05912	0.07956	0.05007
0.29417	0.07448	0.11769	0.19242	0.15116	0.06667	0.07299	0.05173	0.06252	0.05007
0.29417	0.09164	0.13731	0.19242	0.15366	0.11518	0.11069	0.05912	0.06252	0.05633
0.29417	0.10880	0.21577	0.23544	0.20571	0.11518	0.14084	0.05912	0.07956	0.06884
0.25305	0.12596	0.21577	0.20333	0.17454	0.11518	0.12576	0.06651	0.07104	0.05007
0.26887	0.10880	0.11102	0.19242	0.15366	0.07884	0.07299	0.05173	0.04549	0.05007
0.26887	0.09164	0.11102	0.18407	0.15116	0.09701	0.08053	0.05173	0.05400	0.05007
0.26887	0.06298	0.10789	0.18728	0.14960	0.06667	0.07042	0.03695	0.05400	0.03442
0.25305	0.06298	0.11102	0.18407	0.15116	0.07884	0.07299	0.03325	0.04549	0.05007

0.29417	0.06298	0.10789	0.18193	0.15366	0.06667	0.07042	0.04434	0.03978	0.03755
Border Approximation area values									
0.293336	0.087176	0.138440	0.206829	0.169983	0.090391	0.090845	0.050296	0.057878	0.048949

Table 15: Distance of option`s performance from the border approximation area matrix

DSA	EAI	IR	CSC	CBT	LRC	ASS	CET	ME	SFR
0.212764	0.021625	0.077332	0.157030	0.129227	0.042953	0.034920	0.008821	0.021679	0.001120
0.000835	-0.012697	-0.020747	-0.014412	-0.018820	-0.023719	-0.017859	0.001431	0.004643	0.001120
0.000835	0.004464	-0.001131	-0.014412	-0.016326	0.024786	0.019840	0.008821	0.004643	0.007378
0.000835	0.021625	0.077332	0.028609	0.035724	0.024786	0.049999	0.008821	0.021679	0.019895
-0.040286	0.038786	0.077332	-0.003496	0.004556	0.024786	0.034920	0.016210	0.013161	0.001120
-0.024470	0.021625	-0.027416	-0.014412	-0.016326	-0.011547	-0.017859	0.001431	-0.012393	0.001120
-0.024470	0.004464	-0.027416	-0.022759	-0.018820	0.006619	-0.010319	0.001431	-0.003875	0.001120
-0.024470	-0.024195	-0.030554	-0.019548	-0.020378	-0.023719	-0.020423	-0.013348	-0.003875	-0.014527
-0.040286	-0.024195	-0.027416	-0.022759	-0.018820	-0.011547	-0.017859	-0.017043	-0.012393	0.001120
0.000835	-0.024195	-0.030554	-0.024899	-0.016326	-0.023719	-0.020423	-0.005959	-0.018100	-0.011398

Table 17: Final values of matrix

Criteria	Q values	Ranking
DSP	0.70746981	1
EAI	-0.10022501	6
IR	0.03889782	4
CSC	0.289304814	2
CBT	0.167088518	3
LRC	-0.10024811	7
ASS	-0.09402527	5
CET	-0.19503799	10
ME	-0.19119833	9
SFR	-0.1747381	8

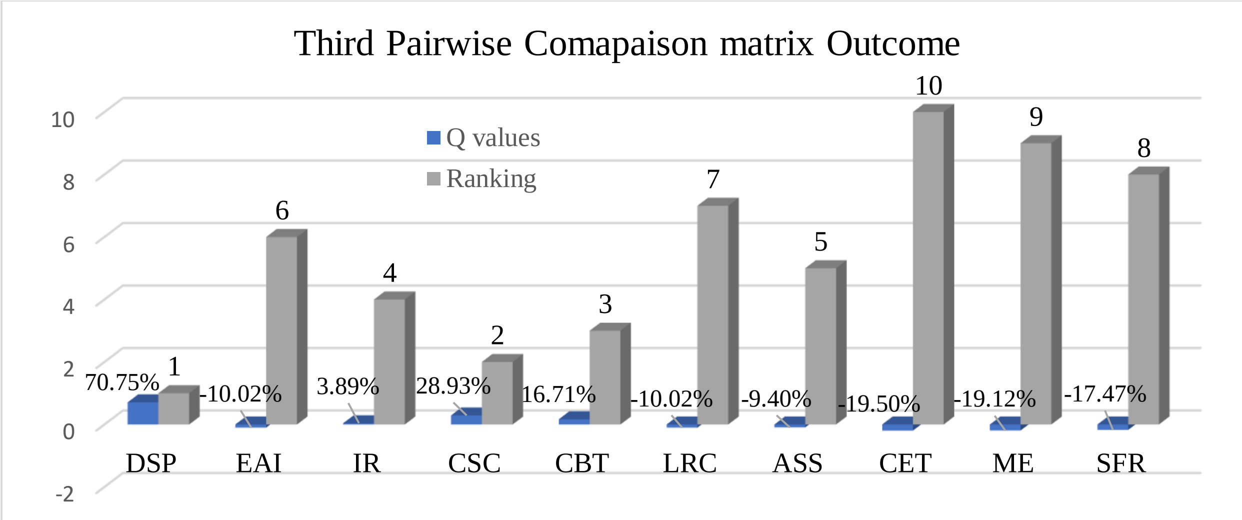

Figure 13: Third pairwise comparison matrix result.

As we obtained weights and ranking of all three pairwise comparison matrices, now we have to synthesize all the above results to get a single ranking of all the key critical success factors.

3.5 RPM ranking

After obtaining the position of each criterion by MABAC method but with three different pairwise comparison matrices and weights. We get the varying results. To get an accurate outcome of position of each criterion we applied the rank position method which gives results elucidated in Table 16.

Table 17: RPM Ranking of all three pairwise comparison matrices

Criteria	QVALUE-01	QVALUE-02	QVALUE-03	RPM	RANKING
DSP	0.682160	0.433835	0.707470	0.1929	1
EAI	-0.127487	-0.027709	-0.100225	-0.0186	4
IR	0.194917	-0.022482	0.038898	-0.0719	9
CSC	0.227980	0.533499	0.289305	0.1029	2
CBT	0.218660	0.150067	0.167089	0.0581	3
LRC	0.018163	-0.019460	-0.100248	-0.1609	10
ASS	-0.147348	-0.123828	-0.094025	-0.0392	5
CET	-0.193732	-0.184832	-0.195038	-0.0637	6
ME	-0.190694	-0.208844	-0.191198	-0.0655	7
SFR	-0.281799	-0.214034	-0.174738	-0.0718	8

4. RESULTS AND DISCUSSIONS

Data Security and Privacy were consistently valued across all measures given by each decision maker, highlighting their importance in humanitarian contexts. Capacity Building and Training gained prominence in one matrix, emphasizing the need for skilled professionals. The Cross-Sector Collaboration appeared to be one of the significant important critical success factors (CSFs) based on the pairwise assessment investigation. Effective cooperation is indispensable for addressing multifaceted humanitarian encounters and leveraging the fortes of diverse establishments. Defending sensitive information is dynamic to avoid mistreatment and safeguard the secrecy of susceptible populations. Advancing training plans can train humanitarian workers with the services desirable to excellently employ digital tools and AI. Adhering to relevant laws and regulations is essential for ethical and responsible AI implementation. Advance in healthy infrastructure to guarantee the provision of humanitarian aid and facilities. Encourage collaboration between humanitarian organizations, governments, technology companies, and other stakeholders. There is always a need to device strong cybersecurity measures and ethical AI practices to protect sensitive data. Provide training programs to equip humanitarian workers with the necessary skills and knowledge. Stay updated on relevant laws and regulations and implement measures to ensure compliance. EAI, ASS, CET, ME, and SFR have relatively low rankings, suggesting they are less critical in this context. Legal and Regulatory Compliance was consistently considered important, reflecting the ethical and legal considerations in AI implementation. Infrastructure Resilience fundamentally investing in robust infrastructure is crucial for ensuring the delivery of humanitarian aid and services in crisis situations.

The provided table 17 presents the results of a ranking using the ranking method (RPM) based on three pairwise comparison matrices (see Fig. 14). These matrices likely represent comparisons between different criteria or factors within a specific context. The RPM scores and rankings in the table indicate the relative importance of each criterion. A higher RPM score and a lower ranking position suggest greater importance. Based on the data, DSP is ranked the highest, indicating it is considered the most important criterion. LRC is ranked the lowest, suggesting it is the least important.

The QVALUE-01, QVALUE-02, and QVALUE-03 columns likely represent the results of pairwise comparisons using different perspectives or criteria. Analyzing these values can provide insights into the specific factors that contributed to the final ranking. DSP consistently has higher QVALUE values across all three matrices, it suggests that it was consistently favored over other criteria.

4.1 Key Observations

- DSP consistently has positive QVALUE values, indicating it's favored over other criteria.
- LRC consistently has negative QVALUE values, indicating it's less favored.
- IR has mixed QVALUE values, suggesting its importance varies depending on the perspective.
- EAI, ASS, CET, ME, and SFR have relatively low rankings, suggesting they are less critical in this context

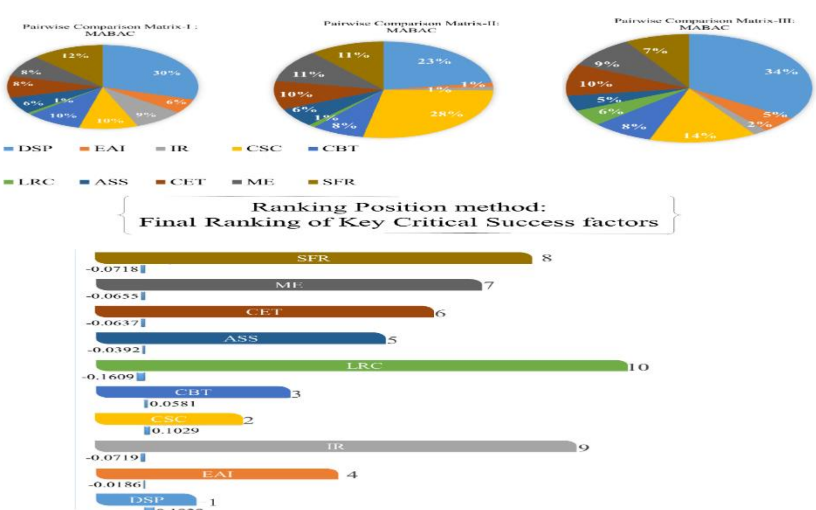

Figure 14: Preferences of key Critical success factors with MABAC and final RPM result.

5. CONCLUSION WITH FUTURE RECOMMENDATIONS

The proposed hybrid decision-making model, combining AHP and MABAC, effectively identified and ranked the critical success factors (CSFs) in the context of digitization, AI, and cyber warfare. The model highlights the importance of Infrastructure Resilience, Cross-Sector Collaboration, and Data Security and Privacy as key factors influencing humanitarian outcomes. Infrastructure resilience is paramount for ensuring the effective delivery of humanitarian aid and services in the face of digital disruptions and cyber threats. Fostering cross-sector collaboration can facilitate knowledge sharing, resource mobilization, and coordinated responses to crises. Strengthening data security and privacy is essential to protect sensitive data and prevent misuse. Investing in capacity building and training can equip humanitarian workers with the necessary skills and knowledge. Adhering to legal and regulatory compliance is crucial for ensuring ethical and responsible AI implementation. Future research can delve deeper into the specific implications of AI and cyber warfare on humanitarian settings. Case studies can be conducted to analyze the effectiveness of the proposed model in real-world contexts. Sensitivity analysis can assess the impact of changes in weights assigned to the criteria. Integrating additional factors, such as cultural context, political stability, and economic conditions, can provide a more comprehensive understanding of the factors influencing humanitarian outcomes. By addressing these areas, future research can contribute to a more comprehensive understanding of the critical success factors and their implications for humanitarian efforts in the digital age.

Conflict of Interest: The authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent: Informed consent was obtained from all individual participants included in the study.

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