Rational Decision-Making in Purchasing Medical Devices

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Abstract

Medical device procurement is a complex process that involves the selection of the product and its supplier. Hospital management tends to make medical device purchasing decisions by predominantly relying on healthcare professionals' experiences and observational trials on the devices. This study proposes a decision support model to purchase medical devices and compares the findings from different approaches. The study uses TOPSIS and fuzzy-TOPSIS methods to evaluate six mechanical ventilators under eight criteria. The results revealed that TOPSIS and fuzzy-TOPSIS approaches ranked alternatives in the same order at each scenario, except the fourth and fifth alternatives being in different ranking order. This study, once again, highlights the value of MCDM methods in rational decision making in purchasing medical devices. The study suggests that integrating fuzzy logic, gathering a team of experts and determining multiple scenarios have value in supporting decision-making.

Keywords
Decision-making, Medical devices, TOPSIS and fuzzy-TOPSIS.

1. Introduction
Medical device procurement is a complex process requiring reliable analysis techniques to make decisions (Keller, 2019). As part of the procurement process, hospital management determines the most suitable device and supplier among alternatives (Ahmadi, Pishvaee and Torabi, 2018). At this point, hospital management tends to make medical device purchasing decisions by predominantly relying on healthcare professionals' experiences or observational trials on the devices (Branson and Johannigman, 2004; Thille *et al.*, 2010).

Several researchers and practitioners proposed approaches to support decision-making in evaluating medical devices. Chatburn and Primiano (2001) offered a decision analysis tool to assess mechanical ventilators. Some suggested ranking suppliers by using a score from 0 (no match) to 4 (very strong match) under multiple criteria (Team Consiliso, 2018). While the scoring mechanism might also support decision-making, Multi-Criteria Decision-Making (MCDM) methods, built on mathematical models, would provide more solid suggestions. MCDM methods propose an ideal solution to complex decision-making problems. For instance, Ivlev, Vacek and Kneppo (2015) used Analytical Hierarchy Process (AHP) to select an MRI system, Tolga, Parlak and Castillo (2020) used fuzzy TODIM to evaluate medical imaging devices, and Sloane *et al.* (2003) used AHP to select a neonatal mechanical ventilator.

MCDM methods have already been used to support clinical and non-clinical decision-making (Marsh et al., 2017). However, the need for using MCDM has been boosted during the COVID-19 pandemic. With the pandemic, decision-makers have been forced to reach rapid decisions under conflicting criteria in a fuzzy environment. For instance, the need for mechanical ventilators increased significantly, and hospital management, in turn, had to deal with procurement in a short time. This study uses an MCDM method to support rational decision-making in purchasing mechanical ventilators under fuzzy and non-fuzzy environments. The study has two objectives: (1) to propose a decision support model to purchase medical devices and (2) compare the findings from different approaches.

2. Methods
This study uses the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and fuzzy TOPSIS method under two different scenarios (i.e., equally-weighted criteria and different weights).

2.1 Criteria Selection

In literature, several criteria were determined to evaluate mechanical ventilators and so medical devices. Chatburn and Primiano (2001) evaluated mechanical ventilators by considering control scheme (i.e., trigger, limit and cycle variables, modes and optional functions) and operator interface (i.e. ease of use) criteria. Team Consiliso (2018) suggested considering seven categories to make medical device procurement decisions: quality system certification, medical device specialty of the firm, manufacturer services of the firm, product development support service, part costs, location and support costs and business fit. Additionally, Grace (1998) claimed that the evaluation of mechanical ventilators requires focusing on needs assessment, education cost, specific ventilator capabilities, maintenance cost and manufacturer support. Similarly, Didier and Helmholz (1964) highlighted the necessity of considering cost, size, application, function, maintenance difficulty, service availability, and the ease of cleaning or sterilizing components, and Keller (2019) advised considering overall performance and safety, ease of use, quality of construction, cost and service and support criteria when evaluating medical devices.

Sloane et al. (2003) identified four top-level criteria: safety, clinical factors, biomedical engineering and cost, to select a neonatal ventilator. Tadić, Stefanović and Aleksić (2014) listed five evaluation criteria: unit cost, delivery time, communication frequency, financial stability and strength, and reliability and conformity of product requirements. Abdel-Basset, Manogaran, Gamal and Smarandache (2019) suggests considering safety, cost, flexibility, ease of use, quality, maintenance requirements and service life to select medical devices.

This study also uses the criteria identified by Abdel-Basset et al. (2019), with adding "availability" as the eighth criterion. During the COVID-19 pandemic, the availability of products became a critical factor in the decisions made. In this study, alternatives are evaluated under two scenarios: weighting each criterion equally and differently. As the application was made with the illustration purpose, the author created a case study hypothetically evaluating six mechanical ventilators under eight criteria.

2.2 TOPSIS

TOPSIS method is built on selecting the alternative closest to the positive ideal solution and farthest to the negative ideal solution (Hwang and Yoon, 1981; Opricovic and Tzeng, 2004). In this study, TOPSIS is explained in eight steps.

Step 1: Identify the decision-making problem, criteria and alternatives
Experts should involve in the process to identify criteria and alternatives. Experts should shortlist alternatives (i=1, 2,.. m) before the evaluation.

Criteria (j=1, 2,..n) can be listed using expert knowledge and existing literature. This study treated all criteria to be benefit criteria. For instance, a score of 1 for the 'cost' criterion represents the alternative being very expensive, and 7 means it to be very cheap. Likewise, a score of 1 for the 'maintenance requirements' criterion represents a vast number of requirements, and 7 refers to a minimal number of requirements. So, maximization was the objective for all criteria.

Step 2: Construct the decision matrix (X)
Alternatives are evaluated based on each criterion. This study used crisp numbers, a score from 1 (very poor) to 7 (very good), to quantify the linguistic descriptions provided in Table 2.

Step 3: Determine the weighting vector (W)
The weights of each criterion can be assigned by using both subjective (e.g., AHP) and objective (e.g., entropy) methods. Subjective weighting requires the involvement of subject matter experts. This study evaluated alternatives under two scenarios. Table 1 shows the weights assigned to each criterion for both Scenario 1 and 2. In Scenario 1, criteria were equally weighted. In Scenario 2, the author assigned predetermined weights to each criterion.

Table 1. The weights of each criterion under two scenarios

Scenarios	C1: Safety	C2: Cost	C3: Flexibility	C4: Ease of use	C5: Quality	C6: Maintenance requirements	C7: Service life	C8: Availability
Scenario 1	$w_1 = 0.125$	$w_2 = 0.125$	$w_3 = 0.125$	$w_4 = 0.125$	$w_5 = 0.125$	$w_6 = 0.125$	$w_7 = 0.125$	$w_8 = 0.125$
Scenario 2	$w_1 = 0.17$	$w_2 = 0.08$	$w_3 = 0.1$	$w_4 = 0.14$	$w_5 = 0.12$	$w_6 = 0.09$	$w_7 = 0.1$	$w_8 = 0.2$

Step 4: Calculate the normalized decision matrix (R)
Vector normalization is used to calculate the R matrix by using Equation (1).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} X_i^2}} \quad (1)$$

Step 5: Calculate the weighted normalized decision matrix (V)
V matrix is represented as in (2), where w_j is the weight of each criterion.

$$V = \begin{bmatrix} w_1r_{11} & w_2r_{12} & \cdots & w_nr_{1n} \\ w_1r_{21} & w_2r_{22} & \cdots & w_nr_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ w_1r_{m1} & w_2r_{m2} & \cdots & w_nr_{mn} \end{bmatrix}_{m\,x\,n} \quad (2)$$

Step 6: Calculate the positive ideal (A^+) and negative ideal (A^-) solutions
$A^+ = (v_1^+, v_2^+, v_j^+ .. v_n^+)$, $v_j^+ = \{max_i\ v_{ij}\}$ if j is a benefit criterion and $v_j^+ = \{min_i\ v_{ij}\}$ if j is a cost criterion.
$A^- = (v_1^-, v_2^-, v_j^- .. v_n^-)$, $v_j^- = \{min_i\ v_{ij}\}$ if j is a benefit criterion and $v_j^- = \{max_i\ v_{ij}\}$ if j is a cost criterion.

Step 7: Calculate the distance from positive ideal (d_i^+) and negative ideal (d_i^-) solutions

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2} \quad (3)$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (4)$$

Step 8: Calculate the closeness coefficient (CC)
CC is calculated for each alternative, and then the value obtained from Equation (5) is used to rank alternatives in descending order.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \quad (5)$$

2.3 Fuzzy- TOPSIS

Fuzzy approach integrated into MCDM methods to manage uncertainty. Fuzzy-TOPSIS would better fit into the decision-making problem once alternatives are qualitatively evaluated using linguistic descriptions (Chen, 2000). This study used triangular fuzzy numbers, which are often used in fuzzy approaches, instead of using crisp values for the linguistic terms (Table 2).

Table 2. Linguistic terms and corresponded crisp values and fuzzy numbers (Wang and Lee, 2009)

Linguistic terms	Crisp values	Fuzzy numbers
Very poor (VP)	1	(0, 0, 0.2)
Poor (P)	2	(0.05, 0.2, 0.35)
Medium poor (MP)	3	(0.2, 0.35, 0.5)
Fair (F)	4	(0.35, 0.5, 0.65)
Medium good (MG)	5	(0.5, 0.65, 0.8)
Good (G)	6	(0.65, 0.8, 0.95)
Very good (VG)	7	(0.8, 1, 1)

Fuzzy- TOPSIS follows the same fundamental steps explained in Section 2.1 by using fuzzy numbers. In the first step, criteria (j=1,2,.. n) and alternatives (i=1,2,.. m) are identified. In the second step, a decision matrix ($\widetilde{D}$) is constructed using the triangular fuzzy numbers in Table 2. Here, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$. If there are K decision-makers, $\tilde{x}_{ij}$ values are calculated as in Equation (6).

$$\tilde{x}_{ij} = \frac{1}{K}\left[\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + .. \tilde{x}_{ij}^K\right] \quad (6)$$

In the third step, the weight of each criterion is calculated. In this study, predetermined weights were assigned to each criterion. In the fourth step, the normalized decision matrix ($\tilde{R}= [\tilde{r}_{ij}]_{mxn}$) is calculated by following Equation (7).

$$\begin{aligned} \tilde{r}_{ij} &= \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), if\ j\ is\ a\ benefit\ criterion. \quad c_j^* = max_i c_{ij} \\ \tilde{r}_{ij} &= \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), if\ j\ is\ a\ cost\ criterion. \quad a_j^- = min_i a_{ij} \end{aligned} \tag{7}$$

In the fifth step, weighted normalized decision matrix ($\tilde{V} = [\tilde{v}_{ij}]_{mxn}$) is calculated. In this study, $\tilde{v}_{ij} = \tilde{r}_{ij}(.)w_j$. In the sixth step, positive ideal (A^+) and negative ideal (A^-) solutions are estimated, shown in Equation (8).

$$\begin{aligned} A^+ &= (\tilde{v}_1^+, \tilde{v}_2^+, .. \tilde{v}_n^+),\ \tilde{v}_j^+ = (1,1,1) \\ A^- &= (\tilde{v}_1^-, \tilde{v}_2^-, .. \tilde{v}_n^-),\ \tilde{v}_j^- = (0,0,0) \end{aligned} \tag{8}$$

In the seventh step, the distance from the positive ideal (d_i^+) and negative ideal (d_i^-) solutions are estimated as in Equation (9).

$$\begin{aligned} d_i^+ &= \textstyle\sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+) \\ d_i^- &= \textstyle\sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \end{aligned} \tag{9}$$

Equation (9), d(. , .) refers to the distance between two fuzzy numbers. The distance between $\tilde{m}$ and $\tilde{n}$ (d($\tilde{m}$, $\tilde{n}$)) is calculated by Equation (10).

$$d\ (\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]} \tag{10}$$

In the final step, Equation (5) is used to calculate the closeness coefficient and rank alternatives.

3. Results and Discussion

3.1 TOPSIS results

In this study, the author hypothetically evaluated six mechanical ventilators under eight criteria. Table 3 represents the decision matrix.

Table 3. Decision matrix

Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	5	4	4	5	4	6	4	5
MV2	5	4	5	5	4	4	5	2
MV3	6	3	6	6	4	4	5	3
MV4	7	7	4	5	5	5	6	5
MV5	5	6	5	6	7	5	6	4
MV6	5	5	4	5	6	4	5	3

Equation (1) was used to calculate the normalized decision matrix in Table 4, and weighted normalized decision matrices were shown in Table 5. Weighted normalized decision matrices were calculated by using the weights provided in Table 1.

Table 4. Normalized decision matrix

Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	0.368	0.326	0.346	0.381	0.318	0.518	0.313	0.533
MV2	0.368	0.326	0.432	0.381	0.318	0.346	0.392	0.213
MV3	0.441	0.244	0.518	0.457	0.318	0.346	0.392	0.320
MV4	0.515	0.570	0.346	0.381	0.398	0.432	0.470	0.533
MV5	0.368	0.488	0.432	0.457	0.557	0.432	0.470	0.426
MV6	0.368	0.407	0.346	0.381	0.477	0.346	0.392	0.320

Table 5. Weighted normalized decision matrix for scenarios 1 and 2

Scenario 1								
Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	0.0460	0.0407	0.0432	0.0477	0.0398	0.0648	0.0392	0.0666
MV2	0.0460	0.0407	0.0540	0.0477	0.0398	0.0432	0.0490	0.0267
MV3	0.0551	0.0305	0.0648	0.0572	0.0398	0.0432	0.0490	0.0400
MV4	0.0643	0.0712	0.0432	0.0477	0.0497	0.0540	0.0587	0.0666
MV5	0.0460	0.0610	0.0540	0.0572	0.0696	0.0540	0.0587	0.0533
MV6	0.0460	0.0509	0.0432	0.0477	0.0597	0.0432	0.0490	0.0400
Scenario 2								
Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	0.0625	0.0260	0.0346	0.0534	0.0382	0.0466	0.0313	0.1066
MV2	0.0625	0.0260	0.0432	0.0534	0.0382	0.0311	0.0392	0.0426
MV3	0.0750	0.0195	0.0518	0.0640	0.0382	0.0311	0.0392	0.0640
MV4	0.0875	0.0456	0.0346	0.0534	0.0477	0.0389	0.0470	0.1066
MV5	0.0625	0.0391	0.0432	0.0640	0.0668	0.0389	0.0470	0.0853
MV6	0.0625	0.0326	0.0346	0.0534	0.0573	0.0311	0.0392	0.0640

After calculating A^+ and A^- solutions, d_i^+, d_i^- and CC values were calculated in Table 6. CC values were ranked in descending order to rank alternatives.

Table 6. Ranking alternatives for TOPSIS in scenario 1 and 2

Alternatives	Scenario 1				Scenario 2			
	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
MV1	0.0557	0.0466	0.455	3	0.050	0.066	0.570	3
MV2	0.0673	0.0178	0.209	6	0.080	0.013	0.143	6
MV3	0.0625	0.0303	0.326	5	0.061	0.033	0.349	5
MV4	0.0327	0.0647	0.664	2	0.029	0.076	0.724	2
MV5	0.0292	0.0569	0.661	1	0.035	0.059	0.626	1
MV6	0.0518	0.0329	0.389	4	0.058	0.032	0.357	4

3.2 Fuzzy-TOPSIS results

The same decision-making problem is solved by fuzzy-TOPSIS. First, the decision matrix was constructed by using triangular fuzzy numbers in Table 7. Having used Equation (7), the normalized decision matrix was represented in Table 8. Table 9 provides the weighted normalized decision matrices for both scenarios, and Table 10 shows the fuzzy-TOPSIS findings.

Table 7. Decision matrix for fuzzy TOPSIS

Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	(0.5,0.65,0.8)	(0.35,0.5,0.65)	(0.35,0.5,0.65)	(0.5,0.65,0.8)	(0.35,0.5,0.65)	(0.65,0.8,0.95)	(0.35,0.5,0.65)	(0.5,0.65,0.8)
MV2	(0.5,0.65,0.8)	(0.35,0.5,0.65)	(0.5,0.65,0.8)	(0.5,0.65,0.8)	(0.35,0.5,0.65)	(0.35,0.5,0.65)	(0.5,0.65,0.8)	(0.05,0.2,0.35)
MV3	(0.65,0.8,0.95)	(0.2,0.35,0.5)	(0.65,0.8,0.95)	(0.65,0.8,0.95)	(0.35,0.5,0.65)	(0.35,0.5,0.65)	(0.5,0.65,0.8)	(0.2,0.35,0.5)
MV4	(0.8,1,1)	(0.8,1,1)	(0.35,0.5,0.65)	(0.5,0.65,0.8)	(0.5,0.65,0.8)	(0.5,0.65,0.8)	(0.65,0.8,0.95)	(0.5,0.65,0.8)
MV5	(0.5,0.65,0.8)	(0.65,0.8,0.95)	(0.5,0.65,0.8)	(0.65,0.8,0.95)	(0.8,1,1)	(0.5,0.65,0.8)	(0.65,0.8,0.95)	(0.35,0.5,0.65)
MV6	(0.5,0.65,0.8)	(0.5,0.65,0.8)	(0.35,0.5,0.65)	(0.5,0.65,0.8)	(0.65,0.8,0.95)	(0.35,0.5,0.65)	(0.5,0.65,0.8)	(0.2,0.35,0.5)

Table 8. Normalized decision matrix for fuzzy TOPSIS

Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	(0.5,0.65,0.8)	(0.35,0.5,0.65)	(0.37,0.53,0.68)	(0.53,0.68,0.84)	(0.35,0.5,0.65)	(0.68,0.84,1)	(0.37,0.53,0.68)	(0.63,0.81,1)
MV2	(0.5,0.65,0.8)	(0.35,0.5,0.65)	(0.53,0.68,0.8)	(0.53,0.68,0.84)	(0.35,0.5,0.65)	(0.37,0.53,0.68)	(0.53,0.68,0.84)	(0.06,0.25,0.44)

MV3	(0.65,0.8,0.95)	(0.2,0.35,0.5)	(0.68,0.84,1)	(0.68,0.84,1)	(0.35,0.5,0.65)	(0.37,0.53,0.68)	(0.53,0.68,0.84)	(0.25,0.44,0.63)
MV4	(0.8,1,1)	(0.8,1,1)	(0.37,0.53,0.68)	(0.53,0.68,0.84)	(0.5,0.65,0.8)	(0.53,0.68,0.84)	(0.68,0.84,1)	(0.63,0.81,1)
MV5	(0.5,0.65,0.8)	(0.65,0.8,0.95)	(0.53,0.68,0.84)	(0.68,0.84,1)	(0.8,1,1)	(0.53,0.68,0.84)	(0.68,0.84,1)	(0.44,0.63,0.81)
MV6	(0.5,0.65,0.8)	(0.5,0.65,0.8)	(0.37,0.53,0.68)	(0.53,0.68,0.84)	(0.65,0.8,0.95)	(0.37,0.53,0.68)	(0.53,0.68,0.84)	(0.25,0.44,0.63)

Table 9. Weighted normalized decision matrices for both scenarios

Scenario 1								
Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	(0.06,0.08,0.1)	(0.04,0.06,0.08)	(0.05,0.07,0.09)	(0.07,0.09,0.11)	(0.04,0.06,0.08)	(0.09,0.11,0.13)	(0.05,0.07,0.09)	(0.08,0.1,0.13)
MV2	(0.06,0.08,0.1)	(0.04,0.06,0.08)	(0.07,0.09,0.11)	(0.07,0.09,0.11)	(0.04,0.06,0.08)	(0.05,0.07,0.09)	(0.07,0.09,0.11)	(0.01,0.03,0.05)
MV3	(0.08,0.1,0.12)	(0.03,0.04,0.06)	(0.09,0.11,0.13)	(0.09,0.11,0.13)	(0.04,0.06,0.08)	(0.05,0.07,0.09)	(0.07,0.09,0.11)	(0.03,0.05,0.08)
MV4	(0.1,0.13,0.13)	(0.1,0.13,0.13)	(0.05,0.07,0.09)	(0.07,0.09,0.11)	(0.06,0.08,0.1)	(0.07,0.09,0.11)	(0.09,0.11,0.13)	(0.08,0.1,0.13)
MV5	(0.06,0.08,0.1)	(0.08,0.1,0.12)	(0.07,0.09,0.11)	(0.09,0.11,0.13)	(0.1,0.13,0.13)	(0.07,0.09,0.11)	(0.09,0.11,0.13)	(0.05,0.08,0.1)
MV6	(0.06,0.08,0.1)	(0.08,0.1,0.12)	(0.05,0.07,0.09)	(0.07,0.09,0.11)	(0.08,0.1,0.12)	(0.05,0.07,0.09)	(0.07,0.09,0.11)	(0.03,0.05,0.08)
Scenario 2								
Alternatives	Criteria							
	C1	C2	C3	C4	C5	C6	C7	C8
MV1	(0.09,0.11,0.14)	(0.03,0.04,0.05)	(0.04,0.05,0.07)	(0.07,0.1,0.12)	(0.04,0.06,0.08)	(0.06,0.08,0.09)	(0.04,0.05,0.07)	(0.13,0.16,0.2)
MV2	(0.09,0.11,0.14)	(0.03,0.04,0.05)	(0.05,0.07,0.08)	(0.07,0.1,0.12)	(0.04,0.06,0.08)	(0.03,0.05,0.06)	(0.05,0.07,0.08)	(0.01,0.05,0.09)
MV3	(0.11,0.14,0.16)	(0.02,0.03,0.04)	(0.07,0.08,0.1)	(0.1,0.12,0.14)	(0.04,0.06,0.08)	(0.03,0.05,0.06)	(0.05,0.07,0.08)	(0.05,0.09,0.13)
MV4	(0.14,0.17,0.17)	(0.06,0.08,0.08)	(0.04,0.05,0.07)	(0.07,0.1,0.12)	(0.06,0.08,0.1)	(0.05,0.06,0.08)	(0.07,0.08,0.1)	(0.13,0.16,0.2)
MV5	(0.09,0.11,0.14)	(0.05,0.06,0.08)	(0.05,0.07,0.08)	(0.1,0.12,0.14)	(0.1,0.13,0.13)	(0.05,0.06,0.08)	(0.07,0.08,0.1)	(0.09,0.13,0.16)
MV6	(0.09,0.11,0.14)	(0.04,0.05,0.06)	(0.04,0.05,0.07)	(0.07,0.1,0.12)	(0.08,0.1,0.12)	(0.03,0.05,0.06)	(0.05,0.07,0.08)	(0.05,0.09,0.13)

Table 10. Ranking alternatives for Fuzzy-TOPSIS in scenario 1 and 2

Alternatives	Scenario 1				Scenario 2			
	d_i^+	d_i^-	CC_i	Rank	d_i^+	d_i^-	CC_i	Rank
MV1	7.371	0.644	0.731	3	7.352	0.663	0.754	3
MV2	7.441	0.577	0.654	6	7.461	0.56	0.635	6
MV3	7.378	0.638	0.724	4	7.372	0.645	0.732	4
MV4	7.243	0.769	0.875	2	7.233	0.779	0.886	2
MV5	7.243	0.769	0.875	1	7.258	0.755	0.859	1
MV6	7.381	0.634	0.72	5	7.391	0.625	0.71	5

3.3 Comparison of TOPSIS and fuzzy-TOPSIS

The study used TOPSIS and fuzzy-TOPSIS methods under two different scenarios to compare the findings. Figure 1 represents the findings from the comparison. TOPSIS and fuzzy-TOPSIS methods ranked alternatives in the same order for the specific scenarios, except the 4th and 5th alternatives were ranked differently.

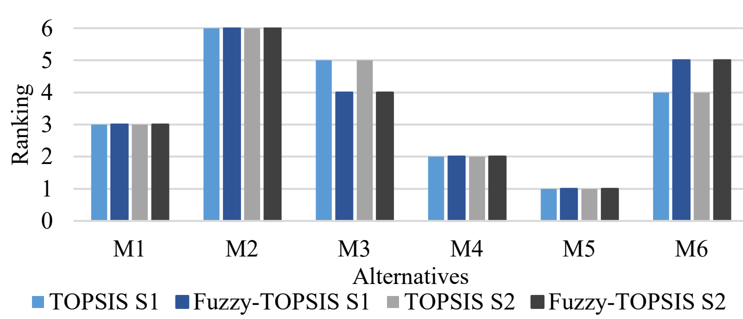

Figure 1. Comparison of TOPSIS and fuzzy-TOPSIS in two scenarios

The findings revealed that different scenarios (i.e., S1 and S2) did not change the rankings in both TOPSIS and fuzzy-TOPSIS. This was because the criteria weights were assigned similarly in both scenarios, and alternatives received similar scores in the decision matrix.
Results suggest that purchasing the M5 would be the ideal choice under the given criteria. At this point, M5 dominates other alternatives. However, different rankings could have been obtained under different scenarios. It is essential to generate several scenarios in rational decision-making to analyze slight changes in the ranking order.

In the literature, researchers made similar comparisons between different methods or the different approaches of the same methods. For instance, Ploskas and Papathanasiou (2019) investigate different approaches in TOPSIS and VIKOR in both fuzzy and non-fuzzy environments. For example, the study described various normalization techniques and different ways of determining positive ideal (A^+) and negative ideal (A^-) solutions. Dağdeviren, Yavuz and Kilinç (2009) compared the findings between weighted and unweighted rankings using fuzzy TOPSIS. It is likely to have different findings using different methods or approaches.

This study used TOPSIS and fuzzy-TOPSIS to provide a case study for the healthcare domain and compare findings from these two approaches. Fuzzy logic, introduced by Zadeh (1965), is used in decision-making to minimize vagueness and address uncertainties (Coroiu, 2015). Hence, researchers suggest using fuzzy logic in decision-making problems by often using triangular (Tadić, Stefanović and Aleksić, 2014), trapezoidal (Tadić, Stefanović and Aleksić, 2014) and gaussian (Tolga, Parlak and Castillo, 2020) membership functions.

Yet, still, decision-making methods have limitations (Asadabadi, Chang and Saberi, 2019; Kaya, 2020). MCDM methods are likely to rank alternatives in a different order, especially the middle ones. This can be better observed when a large number of criteria and alternatives involved in the decision-making problem. While it might not be a problem when selecting a single alternative, it can be a major problem when evaluating all alternatives. Hence, it is essential to strengthening the approaches taken to use MCDM methods. At this point, using fuzzy logic is one way to achieve that. Additionally, forming a team for decision-making is critical to make decisions. Multiple subject matter experts (SME) should involve in the decision-making problem. SMEs should keep in mind that MCDM methods are to support decision making. Therefore, decision-makers should build a consensus to reach a final decision based on the findings.

3.4 Proposed Improvements

Figure 2 represents the proposed approach in eight fundamental steps. In the proposed approach, a facilitator should gather a team for decision-making. It is desirable to have multiple subject matter experts in the team.

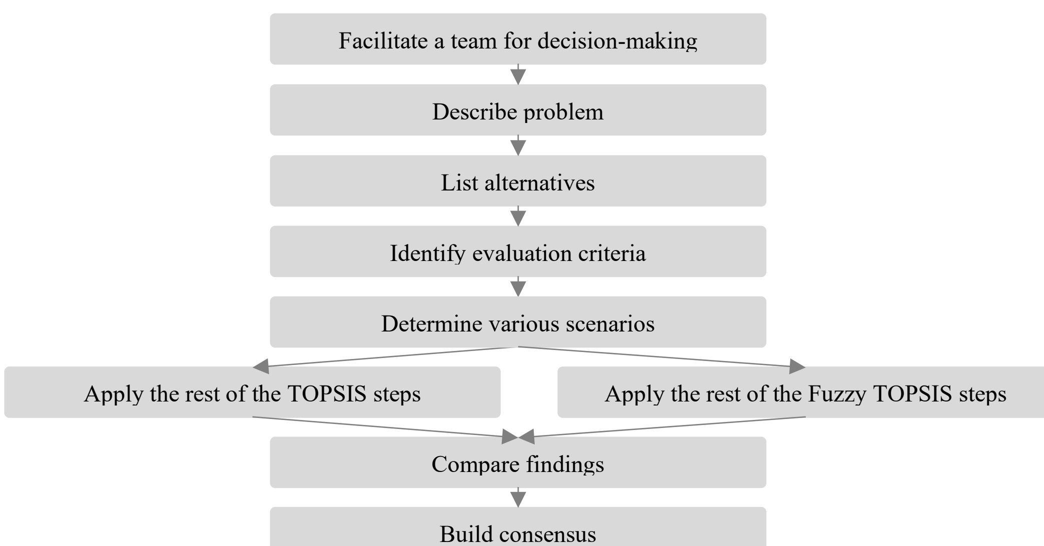

Figure 2. Proposed decision-making approach

Following that, the team should describe the decision problem, shortlist alternatives and identify evaluation criteria. The team should generate various scenarios depending on the nature of the decision-making problem by changing the weight of each criterion. Here, the team might assign weights to each criterion based on their expert judgment or use a technique. Next, the team applies the rest of the TOPSIS and fuzzy-TOPSIS steps to evaluate alternatives. If alternatives have absolute values for each criterion, the team might only use TOPSIS. After obtaining results, the decision-making team compares the findings and builds a consensus on selecting the alternative.

4. Conclusion

The need for quick and rational decision-making has been boosted during the COVID-19 pandemic. Such a need increased the potential value of MCDM methods in healthcare. This study provided a case study for applying TOPSIS and fuzzy-TOPSIS methods in purchasing mechanical ventilators and compared the findings from these two approaches. The results showed that “M5” is the ideal alternative under the given two scenarios. As M5 was ranked first in both scenarios, this represents its dominance among other alternatives.

This study proposed a decision-making approach to overcome the limitations of the MCDM methods. MCDM methods have been used to select, classify or prioritize alternatives. However, their use might not always be reliable. The use of different MCDM methods might lead to different rankings on alternatives. In turn, this would affect the decisions made, especially in prioritizing alternatives. The study suggests that integrating fuzzy logic, gathering a team of experts and determining multiple scenarios could improve the outputs from the MCDM methods.

In conclusion, this study provides a step-by-step guide on applying the proposed approach for rational decision-making. Decision-makers can use the proposed approach in different settings to manage COVID-19 pandemic. Future studies can be conducted by involving multiple subject matter experts actually to evaluate the mechanical ventilators. MCDM methods can also be beneficial to decide which vaccination product to purchase for the national immunization program and enforce COVID-19 restrictions.

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