Selection of Temperature Screening Methods for COVID-19 by Fuzzy TOPSIS Technique

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Abstract

In the COVID-19 pandemic, temperature screening before a person enters a workplace can help to evaluate the patient and limit further spread of the virus. There are two types of temperature screening methods typically used in Thailand: (1) standing infrared thermometer and (2) infrared thermometer gun. This research aimed to use the Fuzzy TOPSIS technique to select the suitable temperature screening methods for 8 screening stations at the case study. Five criteria for the selection of the suitable methods were identified by experts, including cost, accuracy, process waiting time, convenience to use the tool, and customer satisfaction. These criteria were then ranked by staff working at each temperature screening station. Data related to these criteria were collected and input in the Fuzzy TOPSIS technique process. The results showed that the stations that considered the accuracy, process waiting time, and convenience to use the tool as important criteria were suggested to use the standing infrared thermometer. While the remaining stations were suggested to use the infrared thermometer gun. This research can contribute to academic literature as it presents the application of Fuzzy TOPSIS in the activities related to COVID-19 that is currently limited in existing studies.

Keywords
COVID-19, temperature screening, Fuzzy TOPSIS

1. Introduction

Coronavirus Disease (COVID-19) is an infectious disease by the SARS-CoV-2 virus (Baj et al. 2020). The disease has become an international priority since its first identification in late December 2009, in Wuhan, Hubei Province, People's Republic of China (Wu et al. 2020). COVID-19 virus can spread between people who are in close contact with each other. It can spread from an infected person's mouth or nose in small liquid particles when they cough, sneeze, speak, or breath. Another person can then contact the virus when infectious particles that pass through the air are inhaled at a short-range or if infectious particles come into direct contact with the eyes, nose, or mouth (Wright and Mackowiak 2020)

COVID-19 easily spreads especially in a workplace where many people are gathered. One measure to reduce the risk of a person introducing COVID-19 into a workplace is to take the temperature of any people before they enter a workplace. The temperature screening helps to identify persons who have an evaluated temperature of 38°C or higher, which is one of the symptoms of COVID-19 (Wright and Mackowiak 2020)

There are two types of temperature screening typically used in Thailand – where the case study of this research is located – (1) a temperature screening with a standing infrared thermometer, called in this paper as an automatic system; and (2) temperature screening with an infrared gun, called as a manual system because the infrared gun must be used by staff at the screening station.

In the case study, there were 8 temperature screening stations and the management allowed staff at each station to select the temperature screening method itself. As a result, two stations used the automatic system while six stations used the manual one. Based on the observation, there were some problems in the operations of temperature screening, such as high numbers of customers waiting for temperature screening due to the operation delays, differences in operation cost at each station according to the selection of temperature screening system, as well as safety of staff at each temperature screening station. These problems led to the questions of this research:

- What are the criteria that should be considered for selecting the temperature screening method for each station?
- What is a suitable temperature screening method for those stations?

From the review of relevant literature, many techniques, such as the Analytical Hierarchy Process (AHP) and Fuzzy Technique for Order Preference by Similarity to an Ideal Solution (Fuzzy TOPSIS), has been widely applied in the multiple criteria decision-making (MCDM) for selecting the best alternative (Taylana et al. 2014). The AHP is a method of "measurement through pairwise comparison and relies on the judgments of experts to derive priority scales" (Russo and Camanho 2015). It is normally used for the consideration of the criteria that cannot measure quantitively. While the Fuzzy TOPSIS is based on the principle that the selected alternative should have the least distance to the positive ideal and the most distance to the negative ideal. Fuzzy TOPSIS, on the other hand, is normally used to consider quantitative criteria (Taylana et al. 2014). Both AHP and Fuzzy TOPSIS techniques are applied in many studies and different activities (Boonmee and Kasemset 2019). For example, Kusumawardani and Agintiara (2015) applied the Fuzzy AHP-TOPSIS method in the selection of human resources. Boonmee et al. (2017) used the AHP to select the mathematical model for evacuation planning. Janjua and Hassan (2020) applied the Fuzzy AHP-TOPSIS method for the ranking of the Industrial reservoir system in Pakistan. Shinde and Bharadwaj (2020) proposed the integrated Fuzzy AHP and Fuzzy TOPSIS to select the hospital. Fuse et al. (2021) proposed the Fuzzy AHP and TOPSIS for parameter optimization problems in alloy machining.

This research aims to consider the quantitative criteria. Therefore, the Fuzzy TOPSIS is selected as the main technique for selecting the temperature screening method for COVID-19 in the case study. Accordingly, this research can potentially contribute to academic literature as it presents the application of Fuzzy TOPSIS in the activities related to COVID-19. This aspect is still limited in existing studies[1] because, firstly, most studies use the Fuzzy TOPSIS in other types of activities such as manufacturing (Alshehri and Albukhari 2021) or location selecting activities (Hamdan and Cheaitou 2015) and, secondly, the COVID-19 has just been identified in late 2019.

The structure of the remaining sections is organized as follows. The second section presents the steps to conduct this research together with concepts used in each step. This is followed by the third section that discusses the results of this research. While the last section provides the conclusion.

2. Methodology

This section presents the steps to conduct this research (Figure 1) together with concepts used in each step.

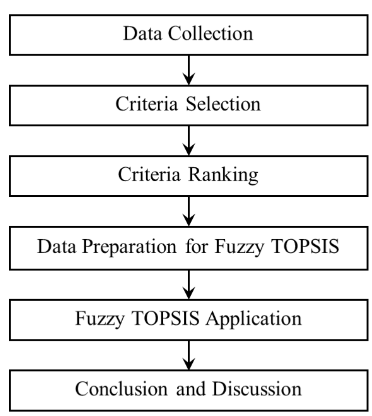


Figure 1. Steps to conduct this research

[1] There are recently published articles applied the Fuzzy TOPSIS and AHP in activities related to COVID-19, for example, Alemdar et al. (2021) used them for selecting vaccine center, Boyacı and Şişman (2022) used them for selecting the hospitals, and Ersoy (2021) used them for selecting equipment.

2.1 Data Collection

The first step was to collect the necessary data. Data of the existing process were collected, including types of temperature screening methods, the screening processes, operation time in each process, as well as the number of customers at each station in a different period. Data in terms of the temperature screening processes were then analyzed to set the same procedure standard for all screening stations.

2.2 Criteria Selection

The second step was to choose the criteria for the selection of temperature screening method. The primary criteria were collected from the surveys and interviews with professionals who have experience in the COVID-19 screening process. Then, these primary criteria were evaluated using the index of Item Objective Congruence (IOC) technique by the selected experts. The experts considered and gave a score including +1, 0, -1 for each candidate criterion. +1 means that the expert strongly agreed that criterion should be included, -1 means that the expert strongly disagreed that criterion should be included, 0 means that the expert was not sure if that criterion should be included in the selection of the screening method.

The IOC scores of each criterion judged by the experts were finally calculated using an equation (1). The criteria that got the IOC scores lower than 0.5 were eliminated. While the criteria that got IOC scores of more than 0.5 were selected as the main criteria for selecting the temperature screening method.

$$\mathrm{IOC} = \sum \mathrm{R}/\mathrm{n} \qquad (1)$$

2.3 Criteria Ranking

The third step was to weigh the importance of the criteria by the ranking method. All criteria derived from the second step were pairwise compared. If one criterion was considered superior to another, that criterion got a score of 1, or if not, the criterion got a score of 0. Once all criteria were compared, each criterion was ranked based on its total score. And finally, the weight of each criterion was calculated using equation (2).

$$w_r = \frac{\frac{1}{r_j}}{\sum_{k=1}^{n} \frac{1}{r_k}} \qquad (2)$$

Where r_j is the rank of the j-th criterion, $j = 1, 2, \ldots, n$.

2.4 Data Preparation for Fuzzy TOPSIS

The fourth step was to prepare data for the Fuzzy TOPSIS technique. As mentioned, data used in the Fuzzy TOPSIS technique should be quantitative data; therefore, this step was about collecting qualitative data related to the criteria for selecting the temperature screening method.

2.5 Fuzzy TOPSIS application

The fifth step was to apply the Fuzzy TOPSIS technique in the selection of the temperature screening method. The Fuzzy TOPSIS views an MCDM problem with m alternatives as a geometric system with m points in the n-dimensional space. The Fuzzy TOPSIS is based on the principle that the chosen alternative should have the shortest distance from the negative ideal solution. TOPSIS defines an index called similarity to the positive-deal solution and the remoteness from the negative-ideal solution. The method, then, selects an alternative with the maximum similarity to the positive-ideal solution (Wang and Chang 2007). It is normally difficult for decision-makers to assign a precise performance rating to an alternative for the attributes under consideration. To merit of using a Fuzzy approach is to assign the relative importance of attributes using Fuzzy numbers instead of precise numbers. This section extends the TOPSIS to the Fuzzy environment (Yang and Hung 2007). This method is particularly suitable for solving the group decision-making problem under a Fuzzy environment.

The Fuzzy TOPSIS method comprises of the following steps (Sun and Lin 2009 and Nădăban et al. 2016), as follows:

Step 1: Create a decision matrix and compute the aggregated Fuzzy ratings for alternatives. The aggregated Fuzzy rating $r_{ij} = (a_{ij}, b_{ij,} c_{ij})$ of i^{th} alternative w.r.t. j^{th} criterion is obtained.

Step 2: Calculate the normalized Fuzzy decision matrix. The normalized Fuzzy decision matrix is calculated as follows:

Positive ideal solution:

$$nr_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right) = \left(nar_{ij}, nbr_{ij,} ncr_{ij}\right);\ c_j^+ = maxc_{ij} \qquad (3)$$

Negative ideal solution:

$$nr_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) = \left(nar_{ij}, nbr_{ij,} ncr_{ij}\right);\ a_j^- = mina_{ij} \qquad (4)$$

Step 3: Calculate the weighted normalized Fuzzy decision matrix. The weighted normalized Fuzzy decision matrix is vr_{ij}, where $vr_{ij} = nr_{ij},, \times w_j$. w_j is the weight of criteria.

Step 4: Determine the Fuzzy Positive Ideal Solution (FPIS: A^*) and Fuzzy Negative Ideal Solution (FNIS: A^-). Where, $A^* = (vr_1{}^*, vr_2{}^*, \dots, vr_n{}^*)$ when $vr_j^* = max_i\{vr_{ji}\}$ and $A^- = (vr_1{}^-, vr_2{}^-, \dots, vr_n{}^-)$ when $vr_j^* = min_i\{vr_{ji}\}$

Step 5: Calculate the distance (d_i^* andd_i^-) from each alternative to the FPIS and the FNIS.
Let:

$$d_{i+} = \sqrt{\frac{1}{3}\left[\left(avr_j{}^* - avrji\right)^2 + \left(bvr_j{}^* - bvrji\right)^2 + \left(cvr_j{}^* - cvrji\right)^2\right]} \qquad (5)$$

$$d_{i-} = \sqrt{\frac{1}{3}\left[\left(avr_j{}^- - avrji\right)^2 + \left(bvr_j{}^- - bvrji\right)^2 + \left(cvr_j{}^- - cvrji\right)^2\right]} \qquad (6)$$

Step 6: Calculate the closeness coefficient (CC_i) for each alternative. For each alternative Ai, we calculate CC_i as follows:

$$cc_i = \frac{d_{i-}}{d_{i+} + d_{i-}} \qquad (7)$$

Step 7: Rank the alternatives according to CC_i

2.6 Conclusion

The last step was to analyze the results from the Fuzzy TOPSIS and to make the conclusion.

3. Results

This section discusses the results of this research following steps explained in the methodology section.

3.1 Data collection

Based on data collected, we found that there were eight temperature screening stations in the present case study (Figure 2). Two Stations – stations A and B – used the standing infrared thermometer or automatic system. While six stations – stations C, D, E, F, G, and H – used the infrared thermometer gun or manual system.

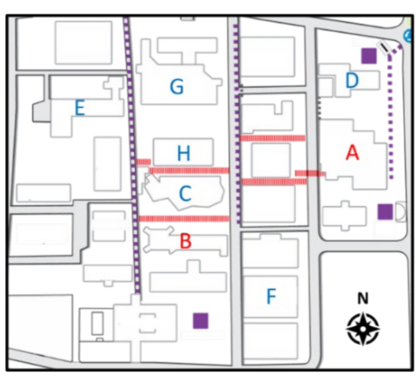


Figure 2. Location of temperature screening stations in the case study (shown in alphabet A-F)

We also found that each temperature screening station operated differently. Therefore, we have consulted with the professionals to set the procedure standard process for all temperature screening stations.

At stations that used the automatic system, the process includes four steps (Figure 3a), including (1) checking body temperature at the standing infrared thermometer (by customer); (2) scanning QR code for temperature record (by customer), (3) scanning QR Code for registration to enter into the buildings (by customer); and (4) attaching symbols, such as color sticks, on the person's clothes for those who have completed the temperature screening process (by staff).

For the manual system (Figure 2b), the process includes (1) checking body temperature using an infrared gun (by staff); (2) attaching symbols, such as color stickers, on the person's clothes for those who have completed the temperature screening process; (by staff) and (3) scanning QR Code for registration to enter into the buildings (by customer).

(1) **(2)** **(3)** **(4)**

3a. Temperature screening process using an automatic system

(1) **(2)** **(3)**

3b. Temperature screening process using a manual system

Figure 3. The standard process for temperature screening

3.2 Criteria Selection

To select the criteria for selecting the temperature screening method, the primary criteria were first collected from the surveys and interviews with professionals. As a result, the primary criteria (Table 1) included location, cost of the tool, spacing of line, accuracy of the tool, process waiting time, convenience to use the tool by staff, the symbol for screening completion, customer satisfaction, and consistency with corporate policy.

After that, these primary criteria were scored using the Index of Item Objective Congruence (IOC) by the experts who have experience in the COVID-19 temperature screening process. After calculating the results of the experts' evaluation by equation (1), the criteria that got the IOC scores lower than 0.5 were eliminated. While the criteria that got IOC scores of more than 0.5 were selected as the main criteria for selecting the temperature screening method. Eventually, five criteria were finally selected: cost of the tool, accuracy of the tool, process waiting time, convenience to use by staff, and customer satisfaction.

Table 1. IOC Score evaluated by experts

Criteria	IOC	Result	Assigned Code
1. Location	0.333	Eliminated	-
2. Cost of tool	0.667	Selected	C1
3. Spacing of line	0.333	Eliminated	-
4. Accuracy of tool	0.500	Selected	C2
5. Process waiting time	0.833	Selected	C3
6. Convenience to use the tool by staff	0.500	Selected	C4
7. Symbol for screening completion	0.167	Eliminated	-
8. Customer satisfaction	0.667	Selected	C5
9. Consistency with corporate policy	0.333	Eliminated	-

3.3 Criteria ranking

Although these 5 criteria were selected, different screening stations valued the importance of these criteria differently. Therefore, the ranking method was adopted to evaluate the importance of each criterion. Based on the evaluation by two staff working at each temperature screening station and the calculation by equation (2), the results were presented in Table 2. As seen, different stations considered the importance of criteria differently.

Table 2. Criteria weights

Criteria code	A	B	C	D	E	F	G	H
C1	0.109	0.109	0.219	0.219	0.219	0.109	0.146	0.109
C2	0.438	0.438	0.146	0.438	0.438	0.219	0.438	0.438
C3	0.219	0.219	0.438	0.146	0.109	0.146	0.219	0.146
C4	0.146	0.146	0.109	0.109	0.146	0.438	0.109	0.219
C5	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088

3.4 Data preparation for Fuzzy TOPSIS

To prepare data for Fuzzy TOPSIS, data related to the selected criteria were collected, as follows:

1. **Cost of tool**
   Cost of the standing infrared thermometer was 9,951 Thai Baht while the infrared gun cost 3,103 Thai Baht.
2. **Accuracy of tool**
   Based on the handbook of the tools, the accuracy of the standing infrared thermometer was ± 0.2 °C and that of the infrared gun was ± 0.3 °C.
3. **Process waiting time:**
   Due to the difficulties in collecting actual waiting time in the process of temperature screening for the whole working period from 8:00 a.m. – 4.00 p.m., the simulation technique was adopted to simulate the process waiting time

   To do that, we have collected data in terms of the number of customers at each temperature screening station at different periods, as shown in Table 3. We also collected 50 data of the operation time of each screening process and fitted the data distribution (Table 4). Based on the P-value, it was found that all fitted distributions can be used to input in the simulation program (At 95% confidence level (95%CI) or $\alpha = 0.05$). We used the Arana 14 program to develop the simulation models, as shown in Figure 3 (3a for temperature screening process using an automatic system and 3b for temperature screening process using a manual system).

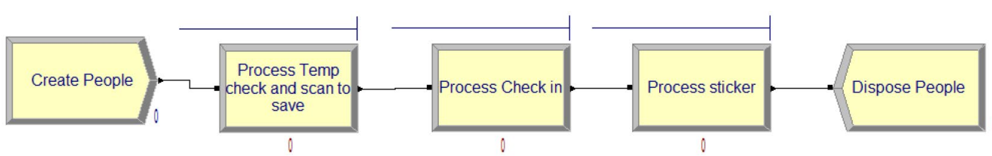
Table 3. The average number of customers per day

Period \ Station	The number of customers at each station							
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**
7.45-8.15 a.m.	98	26	82	24	27	42	63	4
8.15-8.45 a.m.	102	60	13	4	5	29	18	6
8.45-9.15 a.m.	104	19	18	2	3	13	37	15
9.15-10.45 a.m.	209	147	98	1	18	12	12	18
10.45-11.15 a.m.	63	32	37	6	7	63	76	3
11.15-11.45 a.m.	72	37	85	3	12	12	19	2
11.45-12.00 a.m.	8	3	26	2	6	7	1	1
12.45-13.15 p.m.	81	86	106	14	20	47	29	8
13.15-14.45 p.m.	85	242	48	27	51	38	14	2
14.45-15.15 p.m.	22	42	72	18	8	14	9	3
15.15-16.00 p.m.	19	10	25	0	4	7	11	2
Total	863	704	610	101	161	284	289	64

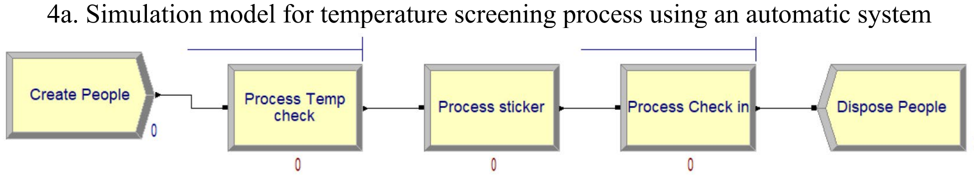
TABLE 4. PROCESS TIME STATISTIC

Process	**Time Distribution**	**P-Value**
Automatic system		
(1) Checking body temperature at the standing infrared thermometer (by customer)*	2.57 + GAMM(0.419, 5.48)	0.287
(2) Scanning QR code for temperature record (by customer)		
(3) Scanning QR Code for registration to enter into the buildings (by customer)	TRIA (1.47,2.35,3.94)	0.671
(4) Attaching symbols	0.51+WEIB (1.17,2.75)	0.407
Manual system		
(1) Checking body temperature using an infrared gun (by staff)	NORM (1.85, 0.448)	0.196
(2) Attaching symbols	TRIA (1.47,2.35,3.94)	0.671
(3) Scanning QR Code for registration to enter into the buildings (by customer)	0.51+WEIB (1.17,2.75)	0.407

* The operation time of process (1) was short and difficult to collect operation time separately; therefore, the operation time of process (1) and (2) were combined.



4a. Simulation model for temperature screening process using an automatic system



4b. Simulation model for temperature screening process using a manual system

Figure 4. The simulation models for generating waiting time

To verify and validate the developed simulation models, we compared the average number of customers from the simulation run with the number of actual customers collected. To generate effective results from the simulation run, the number of replications was determined. 10 replications were run in which each replication was run for 8 hours and 15 minutes. Accordingly, Table 5 compared the average number of customers per day of the actual system, the number of customers from the simulation run at the 95% CI of mean, and percent error from the simulation run at the 95% CI of mean. This research assumed that the error must be less than 10%. As seen, the percent error of all results is less than 10%. This meant that the 10 replications were suitable for the simulation run to generate the process waiting time. Based on the runs from the developed simulation models, the results of the process waiting time at each station were presented in Table 6.

Table 5. Comparison between actual system and simulated system

Station	**The average number of customers**		
	Actual system	**Simulation run**	
		95% CI of the simulation system	**%Error**
A	863	869.50 ± 27.22	3.13
B	704	699.30 ± 18.67	2.66
C	610	612.10 ± 19.07	3.12
D	101	92.90 ± 8.08	8.69
E	161	161.20 ± 11.77	7.3
F	284	287.40 ± 12.34	4.29
G	289	286.20 ± 8.84	3.08
H	64	68.2 ± 6.59	9.52

Table 6. Process waiting time of each location

Station	**Automatic system (minutes)**	**Manual system (minutes)**
A	0.5304 ± 0.04	0.2224 ± 0.02
B	0.7352 ± 0.09	0.3993 ± 0.05
C	2.4475 ± 0.16	1.5889 ± 0.15
D	2.1835 ± 0.27	1.5292 ± 0.17
E	1.8830 ± 0.19	1.2255 ± 0.12
F	2.0641 ± 0.20	1.3791 ± 0.14
G	1.7553 ± 0.15	1.1304 ± 0.09
H	1.1267 ± 0.14	0.7969 ± 0.11

4. **Convenience to use the tool by staff:**
   The convenience to use the tool by staff was evaluated by the staff working at temperature screening stations. Staff could score the convenience score range from 1-5, where 5 was the most convenient to use and 1 was the least convenient to use. The results were tabulated in Table 7.
5. **Customer satisfaction:**
   The customer satisfaction was evaluated from the surveys with the customers at each location. The evaluation scores were ranged from 1 to 5, where 5 was the most satisfying to use and 1 is the least satisfying to use. The results were tabulated in Table 7.

Table 7. The score of convenience and customer satisfaction

Station	**Convenience**		**Customer satisfaction**	
	Automatic	**Manual**	**Automatic**	**Manual**
A	5	3	4.30	3.67
B	5	2	3.62	3.33
C	3	3	3.73	3.67
D	4	4	3.83	3.50
E	3	3	3.60	3.60
F	5	2	3.43	2.85
G	5	3	3.78	3.78
H	5	2	3.33	3.67

3.5 Fuzzy TOPSIS application

When all data for the Fuzzy TOPSIS were prepared, the Fuzzy TOPSIS process was conducted following the steps in the methodology section.

The Triangular Fuzzy Number was set for evaluating each criterion as shown in Table 8 and Table 9.

Table 8. Fuzzy ratings for linguistic variables

Alternative assessment	**Triangular Fuzzy number**
Very poor (VP)	(1, 1, 2)
Poor (P)	(1, 2, 3)
Fair (F)	(2, 3, 4)
Good (G)	(3, 4, 5)
Very good (VG)	(4, 5, 5)

Table 9. Range of linguistic variables

Assessment	**C1***	**C2**	**C3**	**C4**	**C5**
VP	[0,2]	0.1	[0,1]	1	[0,1]
P	(2,4]	0.2	(1,2]	2	(1,2]
F	(4, 6]	0.3	(2,3]	3	(2,3]
G	(6, 8]	0.4	(3,4]	4	(3,4]
VG	(8, 10]	0.5	(4,5]	5	(4,5]

* Unit: 1,000 Thai Baht

To clearly illustrate the steps of Fuzzy TOPSIS in this research, we exemplified the calculation at station G. The linguistic variation of station G was presented in Table 10. Also, the calculation of Fuzzy TOPSIS for location based on two alternatives was tabulated in Table 11. From Table 11., once all criteria were generated the Fuzzy member, the normalized Fuzzy decision matrix was determined by equations (3) and (4). The C1, C2, and C3 were negative ideal solution criteria, while the C4 and C5 were positive ideal solution criteria. The normalized Fuzzy decision of each alternative was present in Row 2 and 3. Then, the normalized Fuzzy decision matrix was multiplied by the weight of each criterion obtained from Section 3.3. The results of the weighted normalized Fuzzy decision matrix were tabulated in Row 5 and 6. The FPIS (A^*) and FNIS (A^-) were then computed based on the two alternatives as shown in Row 8 and 9. As the A^* and A^- of each criterion were identified, the distance (d_i^* and d_i^-) was computed by the equation (5) and (6). The distance of the automatic system was presented in Row 11 and 12 and the distance of the manual system was presented in Row 14 and 15. Finally, the distance was used to calculate the closeness coefficient (CC_i) by equation (7). The distance of each location in each type and the closeness coefficient were presented in Table 12.

Table 10. Linguistic variation for station G

Criteria	Type of tool	Value	Assessment	Fuzzy number		
C1	Automatic	9,951	VG	4	5	5
	Manual	3,103	P	1	2	3
C2	Automatic	0.2	P	1	2	3
	Manual	0.3	F	2	3	4
C3	Automatic	1.75	P	1	2	3
	Manual	1.13	P	1	2	3
C4	Automatic	5	VG	4	5	5
	Manual	3	P	2	3	4
C5	Automatic	3.78	G	3	4	5
	Manual	3.78	G	3	4	5

Table 11. Fuzzy TOPSIS calculation for station G

Row	Type	C1	C2	C3	C4	C5
1	Normalization					
2	Automatic	(1,0.8,0.8)	(1,0.5,0.3)	(1,0.5,0.33)	(0.8,1,1)	(0.6,0.8,1)
3	Manual	(1,0.5,0.33)	(1,0.7,0.5)	(1,0.5,0.33)	(0.5,0.8,0.1)	(0.6,0.8,1)
4	Weighted normalized fuzzy decision matrix					
5	Automatic	(0.146, 0.117, 0.117)	(0.438, 0.219, 0.146)	(0.219, 0.110, 0.073)	(0.087, 0.109, 0.109)	(0.053, 0.070, 0.088)
6	Manual	(0.146, 0.073, 0.049)	(0.438, 0.292, 0.219)	(0.219, 0.110, 0.073)	(0.055, 0.082, 0.109)	(0.053, 0.070, 0.088)
7	FPSI and FNIS					
8	A^*	(0.146, 0.073, 0.049)	(0.438, 0.219, 0.146)	(0.219, 0.110, 0.073)	(0.087, 0.109, 0.109)	(0.053, 0.070, 0.088)
9	A^-	(0.146, 0.117, 0.117)	(0.438, 0.292, 0.219)	(0.219, 0.110, 0.073)	(0.055, 0.082, 0.109)	(0.053, 0.070, 0.088)
10	the distance (d_i^* and d_i^-) from each alternative (Automatic system)					
11	d_{i+}	0.046764	0	0	0	0
12	d_{i-}	0	0.059604	0	0.024575	0
13	the distance (d_i^* and d_i^-) from each alternative (Manual system)					
14	d_{i+}	0	0.059604	0	0.024575	0
15	d_{i-}	0.046764	0	0	0	0

Table 12: Results from Fuzzy TOPSIS

Station	Type of tools	d_{i+}	d_{i-}	$d_{i+} + d_{i-}$	cc_i	Selection
A	Automatic	0.023	0.121	0.143	0.842	Automatic
	Manual	0.121	0.023	0.143	0.158	
B	Automatic	0.035	0.108	0.143	0.756	Automatic
	Manual	0.108	0.035	0.143	0.244	
C	Automatic	0.130	0.020	0.150	0.133	Manual
	Manual	0.020	0.130	0.150	0.867	
D	Automatic	0.090	0.060	0.150	0.398	Manual
	Manual	0.060	0.090	0.150	0.602	
E	Automatic	0.070	0.065	0.135	0.482	Manual
	Manual	0.065	0.070	0.135	0.518	
F	Automatic	0.035	0.200	0.235	0.852	Automatic
	Manual	0.200	0.035	0.235	0.148	
G	Automatic	0.047	0.084	0.131	0.643	Automatic
	Manual	0.084	0.047	0.131	0.357	
H	Automatic	0.035	0.177	0.211	0.835	Automatic
	Manual	0.177	0.035	0.211	0.165	

According to the results, stations A, B, F, G, and H should select the automatic system (standing infrared thermometer) because the staff at these stations considered the accuracy of the tool, process waiting time, and convenience to use of the tool as the crucial criteria for their stations. While stations C, D, and E should select the manual system (infrared thermometer gun).

4. Conclusion and Suggestions for Future Research

This research used the Fuzzy TOPSIS technique to select the suitable temperature screening methods for 8 screening stations at the case study. The research was formulated based on two research questions: what are the criteria that should be considered for selecting the temperature screening method for each station? and what is a suitable temperature screening method for those stations? Five criteria identified by experts for selecting the suitable temperature screening methods consisted of cost, accuracy, process waiting time, convenience to use of the tool, and customer satisfaction. And the results from Fuzzy TOPSIS show that the stations (A, B, F, G, and H) that considered the accuracy, process waiting time, and convenience to use the tool as crucial criteria were suggested to use the standing infrared thermometer, while the remaining stations (C, D, and E) should use the infrared thermometer gun.

This research contributes to academic literature as it demonstrates the application of Fuzzy TOPSIS in the activities related to COVID-19. This aspect is still limited in existing studies because most studies use the Fuzzy TOPSIS in manufacturing or marketing activities. Furthermore, the COVID-19 has just been identified in late 2019. In terms of the suggestions, future research may include perspectives from other parties in the selection of criteria for selecting the temperature screening methods, such as doctors or customers – this research included only the experts who have experience in the process of temperature screening. Including perspectives from other parties may extend this research and result in other criteria that should consider for selecting the temperature screening system. Future research may also apply other techniques, such as AHP or Fuzzy AHP, in the selection of the screening system considering a wide range of criteria. Future research may focus on the uncertainty of criteria and apply the mathematical models to find the optimized solution under the stochastic constraints (Askari et al., 2020; Gharaei et al., 2020; Giri and Masanta, 2020). Additionally, research should further focus on the transfer of modern technologies, e.g., artificial intelligence, machine learning, deep learning (Woschank et al. 2020), and novel simulation approaches, e.g., digital twins (Kaiblinger and Woschank 2022), to the respective domain. The results from those further studies may reveal different perspectives that can add to the value of this research.

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