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The Intuitionistic Fuzzy Analytic Hierarchy Model for Nicotine Replacement Therapy Decision Making Problem

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ABSTRACT

Despite the fact that smoking is the main cause of tobacco-related death, the smoking population continues to rise. To address this problem, Nicotine Replacement Therapy (NRT) was established as a smoking cessation method to reduce the number of smokers. NRT decision-making process requires a large amount of data. However, very little attention has been paid to NRT decision-making using multi-criteria decision-making (MCDM) to assist health decision-makers. To address this issue, a systematic MCDM procedure was utilised to examine the decision-making dilemma in NRT. Both quantitative and qualitative data were used to provide more comprehensive findings. The current work utilised the Intuitionistic Fuzzy Analytic Hierarchy Procedure (IF-AHP) approach to provide a more systematic, comprehensive, and adaptable decision-making process. To capture fuzziness, ambiguity in decision-making, and vagueness of information caused by human language and issue subjectivity, the intuitionistic fuzzy set (IFS) was employed. The present case study illustrated the suggested model's practicality in coping with uncertainty in NRT decision making process. The suggested model fit the local environment and was validated using the NRT decision-making issue. Findings from this study also suggest that the IF-AHP approach is an appropriate decision tool in NRT decision-making process.

Keywords: multi-criteria decision-making; Intuitionistic Fuzzy; Analytic Hierarchy Process; Nicotine Replacement Therapy; decision making

INTRODUCTION

Tobacco is one of the global health threats where it kills more than eight million people every year (World Health Organization, 2021). The use of tobacco kills half of its users and is the second cause of death globally (Ruchi, 2020). Moreover, it is one of the major causes of cancers and preventable diseases such as chronic bronchitis, chronic obstructive pulmonary disease, stroke (Ankita, et. al, 2020). Nowadays, tobacco companies have created cigarettes that contain more nicotine, and the delivery of nicotine is quicker than previous cigarettes. Nicotine is highly addictive, and cigarettes are intended to deliver nicotine to the brain rapidly. This makes it easier to become dependent on nicotine and more difficult to break the habit of smoking. As Ankita et. Al. (2020) argued, nicotine causes both physical and mental addiction which makes the habit of quitting harder for smokers. Additionally, many smokers experience withdrawal symptoms and addictiveness when they try to quit tobacco (Nisha et. al, 2020).

The World Health Organization (WHO) Global Action Plan for the Prevention and Control of Noncommunicable Disease 2013 until 2020 was a turning point in the result of the declining global trends in frequentness of tobacco use (World Health Organization, 2019). All WHO regions show declining tobacco use frequency rates in both age and gender categories. This is due to the help of all parties that took the action to effectively reduce the demand for tobacco. Despite the worldwide decline in tobacco use, development towards achieving the global target to cut tobacco use by 30% by 2025 remains astray. In this regard, there is a need to exar 12 effective and innovative methods of tobacco cessation. Control is very relevant, thus helpful in designing the stop-smoking programmes such as the diagnosing, counselling, preventing, and treating tobacco dependence programmes. One of the methods in tobacco cessation is nicotine replacement therapy already defined earlier in the abstract (NRT). The purpose of NRT is to lessen the withdrawal symptoms by providing other sources of nicotine (Ruchi, 2020). Nicotine gum, nicotine patch, nicotine lozenges, nicotine inhaler, and nicotine nasal spray are examples of NRT products approved by Food and Drug Administration (FDA) and they act as an effective aid to quitting smoking (Ankita et. al, 2020). A study from (Stead et. al, 2012) involving 150 trials on over 50,000 people found that the use of all types of NRT increased the success rate of smoking cessation by 50% to 70%. However, Keane (2013) stated that the use of NRT may ensue different performances of nicotine substance based on the smokers' identity and practice of quitting.

Nowadays, various versions of guidelines for smoking cessation are based on the country's policy (Bader et. al., 2009; Fiore et al., 2008; Hughes, 2013). However, there are no significant differences in the approaches with regard to smoking cessation guidelines. The NRT selection problem involves information systems such as the diversity form of information, subjectivity of information, and more than one decision-maker. Hence, the NRT selection problem involves a multi-criteria decision-making (MCDM) process which is concerned with structuring, solving decision and planning problems involving multiple criteria. Typically, there is no single solution for such problems. In effect, it is necessary to use the health decision maker's preferences to differentiate between solutions. MCDM's purpose is to support decision-makers facing such problems. The basic working principle of any MCDM method is the same: selection of criteria, selection of alternatives, selection of aggregation methods, and ultimately the selection of alternatives based on weights or outranking. The examples of the MCDM method are the Analytical hierarchy Process (AHP) and Elimination and Choice Expressing Reality (ELECTRE).

Based on studies that have been made regarding the NRT selection problem, there is not much research about NRT decisions based on MCDM to help in the selecting problem of NRT as smoking cessation (Bader et. al., 2009; Fiore et al., 2008). Most of the studies just used a guideline and evidence which are still subjective and exposed to human error in the decision-making process. Due to this incomprehensiveness, it will influence the right choice in the NRT selection problem. Since most of the considered criteria are naturally vague, subjective and a diverged input dataset, Intuitionistic Fuzzy – Analytic Hierarchy Process (IF-AHP) is more comprehensive and capable of dealing with uncertainty in MCDM problems was proposed in this study.

In this research, the NRT selecting problem involved a huge amount of information, overlooking the many strands of experience and decision-making process that might involve a complicated process (Zamali et. al., 2013). Therefore, based on the proposed approach, it is believed that the method can deal with the uncertainty of the input dataset in the NRT selection problem. With an attempt to consider the values of hesitation degree, it would be anticipated that the preference scale of matrix judgment makes a more comprehensive compared to the existing method. This preference scale also leads us to the consistency test for matrix judgment by using the values of hesitation degree. The preference scale with a hesitation degree could avoid the decision-makers from repeating the overall process of IF-AHP and the outcome of the decision process would fit the nicotine replacement therapy decision making.

PRELIMINARIES

In this section, some basic important definitions and properties of fuzzy are briefly reviewed:

Definition (i) A fuzzy set *A* in the universe of discourse *X*= $\{x_1, x_2, \ldots, x_n\}$ is defined as:

$$A = \{\langle x, \mu_{\tilde{A}}(x)\rangle x \in X\}$$

which is characterized by the membership function $\mu_{\tilde{A}}(x): X \to [0,1]$, where $\mu_{\tilde{A}}(x)$ indicates the membership degree of the element R to the set *A* (Zadeh, 1965).

Definition (ii) The extension of a fuzzy set to IFS was defined by Atanassov (1986). The Intuitionistic Fuzzy Sets (IFS) concept is defined as follows:
Let *X* be an ordinary finite non-empty set. An IFS in *A* is an expression *A* given by:

$$A = \{\langle x, \mu_x(x), v_x(x)\rangle x \in X\}$$

where, $\mu_x(x): X \to [0,1]$; $v_x(x): X \to [0,1]$ with the condition: $0 \le \mu_x(x) + v_x(x) \le 1$ for all *x* in *X*. The numbers $\mu_x(x)$ and $v_x(x)$ denote, respectively the degree of the membership and non-membership of the element *x* in the set *A*. The notation of IFS '*A*' is defined as follows

$$\pi_x(x) = 1 - \mu_x(x) - v_x(x); \pi_x: X \to [0,1]$$

represents the degree of hesitation or intuitionistic index or non-determinacy of *x* to *A*. Therefore, for ordinary fuzzy sets the degree of hesitation $\pi_x(x) = 0$.

Definition (iii) Given Intuitionistic Fuzzy Weighted Averaging (IFWA) Operator based on Xu (2007): Let $\hat{A}^k = \left(\alpha_{ij}^{(k)}\right)_{m\times n}$ be an intuitionistic fuzzy decision matrix of the *k*th group decision maker. Let $\beta = \{\beta_1, \beta_2, \ldots, \beta_n\}$ be the weights of the all-group decision makers and $\sum_{k=1}^{t}\beta_k$=1∈[0,1] .

$$\alpha_{ij}=\mathrm{IFWA}_\beta\left(\alpha_{ij}^{(1)},\alpha_{ij}^{(2)},\ldots,\alpha_{ij}^{(t)}\right)=\beta_1\alpha_{ij}^{(1)}\oplus\beta_2\alpha_{ij}^{(2)}\oplus\ldots\oplus\beta_t\alpha_{ij}^{(t)}$$
$$=\left(1-\prod_{k=1}^{t}\left(1-\mu_{ij}^{(k)}\right)^{\beta_k},\prod_{k=1}^{t}\left(v_{ij}^{(k)}\right)^{\beta_k},\prod_{k=1}^{t}\left(1-\mu_{ij}^{(k)}\right)^{\beta_k}-\prod_{k=1}^{t}\left(v_{ij}^{(k)}\right)^{\beta_k}\right) \quad (1)$$

Definition (iv) Given Generalized intuitionistic fuzzy weighted geometric (GIFWG) (Xu, 2007). Let $A^k = \left(\alpha_{ij}^{(k)}\right)_{m\times n}$ be an intuitionistic fuzzy decision matrix of the k^{th} group element in matrix. Let $w = \{w_1, w_2, \ldots, w_k\}$ be the weights of the criteria $\sum_{k=1}^{t} w_k$=1∈[0,1]

$$\alpha_{ij}=\mathrm{GIFWG}_\lambda^w\left(\alpha_{ij}^{(1)},\alpha_{ij}^{(2)},\ldots,\alpha_{ij}^{(t)}\right)=\frac{1}{\lambda}\left(\left(\lambda\alpha_{ij}^{(1)}\right)^{w_1}\otimes\left(\lambda\alpha_{ij}^{(2)}\right)^{w_2}\otimes\ldots\otimes\left(\lambda\alpha_{ij}^{(t)}\right)^{w_t}\right)$$
$$\left(\begin{array}{l} 1-\left(1-\prod_{k=1}^{t}\left(1-\left(1-\mu_{ij}^{(k)}\right)^{\lambda}\right)^{w_k}\right)^{\frac{1}{\lambda}},\left(1-\prod_{k=1}^{t}\left(1-v_{ij}^{(k)\lambda}\right)^{w_k}\right)^{\frac{1}{\lambda}}, \\ 1-\left(1-\prod_{k=1}^{t}\left(1-v_{ij}^{(k)\lambda}\right)^{w_k}\right)^{\frac{1}{\lambda}}-1-\left(1-\prod_{k=1}^{t}\left(1-\left(1-\mu_{ij}^{(k)}\right)^{\lambda}\right)^{w_k}\right)^{\frac{1}{\lambda}} \end{array}\right) \quad (2)$$

where λ > 0 is a real number. Furthermore, if $\lambda = 1$, then IFWG operator is a special case of GIFWG operator (Garg, 2016).

Definition (v) Conversion between exact values to intuitionistic fuzzy numbers (IFNs) (Guo, 2013). Let $\dot{a}_{ij}$ be the exact value for the benefit type, the standardizing formula is listed as follows:

$$b_{ij}=\frac{\dot{a}_{ij}}{\sqrt{\sum_{i=1}^{m}\left(\dot{a}_{ij}\right)^2}};i=1,2,\ldots,m;j\in\omega_1 \text{ (benefit-criteria)} \quad (3)$$

For the cost type, the standardizing formula is listed as follows:

$$b_{ij}=\frac{\left(1/\dot{a}_{ij}\right)}{\sqrt{\sum_{i=1}^{m}\left(1/\dot{a}_{ij}\right)^2}};i=1,2,\ldots,m;j\in\omega_2 \text{ (cost-criteria)} \tag{4}$$

Definition (vi) Conversion between intervals values to IFNs (Guo, 2013). Let a_{ij} be interval values for the benefit type, the standardizing formula is listed as follows:

$$b_{ij}^{L}=\frac{a_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left(a_{ij}^{U}\right)^2}} \text{ and } b_{ij}^{U}=\frac{a_{ij}^{U}}{\sqrt{\sum_{i=1}^{m}\left(a_{ij}^{L}\right)^2}};\ i=1,2,\ldots,m;j\in\omega_1 \text{ (benefit-criteria)} \tag{5}$$

For the cost type, the standardizing formula is listed as follows:

$$b_{ij}^{L}=\frac{1/a_{ij}^{U}}{\sqrt{\sum_{i=1}^{m}\left(1/a_{ij}^{L}\right)^2}} \text{ and } b_{ij}^{U}=\frac{1/a_{ij}^{L}}{\sqrt{\sum_{i=1}^{m}\left(1/a_{ij}^{U}\right)^2}};\ i=1,2,\ldots,m;j\in\omega_2 \text{ (cost-criteria)} \tag{6}$$

Definition (vi) Cost-benefit criteria for IFNs (Xu & Hui, 2010) consider an IFN is viewed as $\alpha=(\mu_\alpha,v_\alpha,\pi_\alpha)$ where $\mu_\alpha\in[0,1], v_\alpha\in[0,1]; \mu_\alpha+v_\alpha\le 1, \pi_\alpha=1-\mu_\alpha-v_\alpha$. Then the IFNs for cost criteria as

$$\overline{\alpha}=(v_\alpha,\mu_\alpha,\pi_\alpha) \tag{7}$$

and IFNs for benefit criteria as

$$\alpha=(\mu_\alpha,v_\alpha,\pi_\alpha) \tag{8}$$

Definition (viii) The Intuitionistic Fuzzy Entropy of Aggregated Matrix (Vlachos and Sergiadis, 2007) defined that:

$$\overline{\overline{w}}_i=-\frac{1}{n\ln 2}\left[\mu_i\ln\mu_i+v_i\ln v_i-(1-\pi_i)\ln(1-\pi_i)-\pi_i\ln 2\right] \tag{9}$$

Thus, the final entropy weights of each IF matrix is redefined as:

$$w_i=\frac{1-\overline{\overline{w}}_i}{n-\sum_{i=1}^{n}\overline{\overline{w}}_i} \tag{10}$$

where $\sum_{i=1}^{n} w_i=1$

THE IF-AHP PROCEDURE

This intuitionistic fuzzy set framework was extended from the Saaty's AHP method with IFNs. Similar to the fuzzy AHP and AHP method, the proposed IF-AHP also deal with the relative strength between criterion and alternatives of MCDM problems. The proposed IF-AHP method is described in this section.

Step 1, involve construct hierarchical structure of MCDM problems. Let a general multi-criteria decision problem with m alternatives $A_i(i=1,2,..,m)$ and n criteria, $C_j(j=1,2,..,n)$ can be concisely expressed as $\hat{A}=\left(a_{ij}\right)_{m\times n}$, where the entry $a_{ij}=\mu_{ij},v_{ij},\pi_{ij}$ is an intuitionistic fuzzy number representing the rating of alternative A_i with respect to criterion C_j and W as the weight vector, where w_j represents the weight of criterion C_j.

Step 2, averaging input dataset. This step is special for the decision-making problem which is if there are any; total DMs in each group more than one and there is a sub-criteria in the hierarchy structure. The input data set was based on the total of each GDM by using (1).

Table 1. linguistic variables for the importance of GDMs

Linguistic Variables	IFNs
Very important (VI)	(0.90,0.05,0.05)
Important (I)	(0.75,0.20,0.05)
Medium (M)	(0.50,0.40,0.10)
Unimportant (U)	(0.35,0.60,0.05)
Very unimportance (VU)	(0.10,0.80,0.10)

Step 3, determine the weights of GDMs. Suppose there are k groups of DMs and let $B_k = [\beta_1 \ \beta_2 \ \cdots \ \beta_t]$ be a weighting of k^{th} GDMs matrix, where B is GDM and β is the weight of GDM. The importance of the GDMs is considered as linguistic variables. The defined IFNs for linguistic variables are given in Table 1. Let $\beta_k = (\mu_k, v_k, \pi_k), k = 1, 2, .., t$ be an intuitionistic fuzzy number for the rating of the k^{th} group of decision makers. According to Boran et al., (2009), the weight of the k^{th} group decision maker, β_k can be obtained by using:

$$\beta_k = \frac{\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k + v_k}\right)\right)}{\sum_{k=1}^{t}\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k + v_k}\right)\right)} \tag{11}$$

Step 4, determine the weight of criteria for each of GDMs. There are several steps needed in order to get the weight of criteria for each of the GDMs and let the intuitionistic fuzzy judgment matrix for criteria:

(i) Scaling the pair-wise comparison matrix for criteria
(ii) Construct the aggregated intuitionistic fuzzy judgment matrix for criteria
(iii) Calculate the consistency ratio (*C.R*)
(iv) Calculate the IF weight for criteria.

Step 5, unifying the data input. At this stage, two methods were employed to derive the non-homogenous overall performance dataset into IFNs. At the same time, the normalization processes were derived based on either cost-benefit criteria which were then naturally represented by each of the criteria.
The original data were represented by the crisp value and interval value as per feedback from the expert; the membership function was constructed to derive the IFNs (3), (4), (5) and (6). The original data were represented by the linguistic variable and converted into the IFNs using (7) and (8). The linguistic variable for the ratings and its IFNs based on seven AHP preference scales (Table 2).

Table 2: The linguistic variable for ratings and its IFNs

AHP	Linguistic variables	IFNs		
1	*Very low (VL)*	(0.03,	0.17,	0.8)
2	*Low (L)*	(0.09,	0.21,	0.7)
3	*Medium low (ML)*	(0.21,	0.29,	0.5)
4	*Medium (M)*	(0.34,	0.26,	0.4)
5	*Medium high (MH)*	(0.57,	0.23,	0.2)
6	*High (H)*	(0.77,	0.13,	0.1)
7	*Very high (VH)*	(1,	0,	0)

Step 6, construct the aggregate IF judgment matrix with GDMs' weights. The aggregated IF judgment matrix was constructed respectively with alternatives using the sequence of DM weight value judgment by using (1).
Step 7, involves constructing the overall aggregate IF judgment matrix by using GIFWG operator. The aggregated IF matrix was constructed based on alternatives using the sequence of criteria

weight and parameter $\lambda = 0.5$ by using (2).
Step 8, defuzzification. The aggregated IF entropy weight was used to compute the overall assessment of alternatives by using (9) and (10).
Step 9, rank all the alternatives. Calculate the final value and rank the alternatives based on their arithmetic mean to the final performance value.

ILLUSTRATION OF THE PROPOSED MODEL

To exemplify the concept, the quantitative dataset in this example was based on three decision makers, B_1, B_2 and B_3, a medical officer, pharmacist and patient/smokers, respectively. The selected criteria to evaluate each alternative include {C_1, C_2, C_3, C_4, C_5}: represented by {effectiveness, cost, limitation, dosage, availability}. Let $A_i (i = 1, 2, 3, 4, 5)$ be the alternatives of NRT which may be considered, given as: A_1 is a patch, A_2 is a gum, A_3 is an inhaler, A_4 is a lozenge and A_5 is a nasal spray. Thus, the numerical example technique below demonstrates how to solve the NRT decision-making issue step by step.

Construct the hierarchical structure of MCDM problems

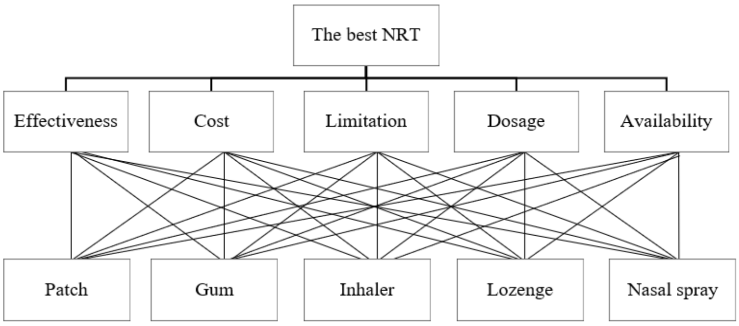

Figure 1. The hierarchical structure for NRT selection problem

As part of the MCDM issue, data for the criteria and alternatives must be identified. Figure 1 illustrates the hierarchical structure of a numerical version of the NRT selection issue. The hierarchical structure is composed of three levels: a goal at the top, criteria in the level 2 and level 3 the alternatives. Based on the entire criteria, C_1, C_2 {effectiveness, cost} are quantitative data as the nature of data is exact and interval figures respectively from experts. Meanwhile, C_3, C_4, C_5 {limitation, dosage, availability} are qualitative data in terms of linguistic figure input data from decision makers. Table 3 shows the quantitative data alternatives and criteria dataset for this decision problem. Meanwhile, Table 4 shows the qualitative data alternatives and criteria dataset by three decision makers B_1, B_2 and B_3 for this NRT selection problem.

Table 3. Quantitative dataset for NRT selection problem

Alternatives	Criteria	
	Benefit criteria Effectiveness (%), C_1	Cost criteria Cost (RM/24 weeks), C_2
Patch, A_1	23.4	[890, 1150]
Gum, A_2	19	[1280, 1700]
Inhaler, A_3	24.8	[1000, 1300]
Lozenge, A_4	24.2	[700, 800]
Nasal spray, A_5	26.7	[2000, 2400]

Table 4. Qualitative dataset for NRT selection problem by all decision makers

	B_1			B_2			B_3		
	C_3	C_4	C_5	C_3	C_4	C_5	C_3	C_4	C_5
	Cost criteria	Benefit criteria		Cost criteria	Benefit criteria		Cost criteria	Benefit criteria	
A_1	L	VH	M	L	VH	M	ML	H	M
A_2	ML	VH	H	ML	VH	M	VL	VH	L
A_3	M	ML	M	MH	L	MH	MH	M	M
A_4	H	H	H	MH	VH	H	H	H	MH
A_5	MH	M	M	H	M	MH	H	M	ML

Averaging input dataset

Averaging input dataset step for if /any; total decision makers in each group are more than one and there are sub-criteria in the hierarchical structure. For this example, the single DM was assumed in each of GDMs and there are no sub-criteria in this decision-making problem. Therefore, the next step is preceded.

Determine the weights of DMs

The importance of the DMs , B_k is considered as linguistic variables. The definition of IFNs for linguistic variables for B_1 , B_2 and B_3 is given in Table 5.

Table 5: The linguistic variable IFNs for weights each DMs

GDMs, $\boldsymbol{B_k}$	Linguistic Variables	IFNs
$\boldsymbol{B_1}$	*Very important (VI)*	(0.90,0.05,0.05)
$\boldsymbol{B_2}$	*Medium (M)*	(0.50,0.40,0.10)
$\boldsymbol{B_3}$	*Very unimportance (VU)*	(0.10,0.80,0.10)

By using (11), the weight obtained for B_1, B_2 and B_3 was $\beta_1 = 0.5870$, $\beta_2 = 0.3442$, and $\beta_3 = 0.0688$, respectively with similar fashion calculation.

Determine the weight of criteria for each of DMs based on pair-wise comparison

There were several steps used in order to get the weight of criteria for each of the DMs:

Scaling the pair-wise comparison matrix for criteria importance

Scaling by using the preference scale of IFNs judgment matrix for criteria. The alphabet '*R*' represents the reciprocal scale of pair-wise comparisons. The abbreviations and preferences scale of IF-AHP shown in Table 6.

Table 6. Pair-wise comparison of criterion

Criteria	C_1	C_2	C_3	C_4	C_5
C_1	*E*	B_1: *RWMI* B_2: *WMI* B_3:*E*	B_1:*WMI* B_2: *VSMI* B_3:*WMI*	B_1: *RVSMI* B_2: *RSMI* B_3:*RWMI*	B_1: *SMI* B_2: *E* B_3: *E*
C_2	B_1 *WMI* B_2: *RWMI* B_3: *E*	*E*	B_1: *RVSMI* B_2: *RVSMI* B_3:*E*	B_1: *E* B_2: *SMI* B_3:*WMI*	B_1: *SMI* B_2: *RWMI* B_3:*WMI*
C_3	B_1:*RWMI* B_2: *RVSMI* B_3:*RWMI*	B_1 *VSMI* B_2: *VSMI* B_3:*E*	*E*	B_1: *RWMI* B_2: *RVSMI* B_3:*RWMI*	B_1: *WMI* B_2: *RWMI* B_3:*E*

Table 6. (continued)

Criteria	C_1	C_2	C_3	C_4	C_5
C_4	B_1:VSMI B_2: SMI B_3:WMI	B_1: E B_2: RSMI B_3:RWMI	B_1:WMI B_2: VSMI B_3:WMI	E	B_1: SMI B_2: RVSMI B_3:RWMI
C_5	B_1:RSMI B_2: E B_3:E	B_1:RSMI B_2: RWMI B_3:RWMI	B_1:RWMI B_2: WMI B_3:E	B_1: RSMI B_2: SMI B_3:WMI	E

Construct the aggregate intuitionistic fuzzy judgment matrix for criteria

The aggregated IF matrix based on weights of the k^{th} GDMs by using (1) and let pairwise comparison for C_1 for all criterion by B_1= (0.56, 0.03, 0.41). Then, the similar fashion of calculation is applied to determine the aggregated matrix for C_2, C_3, C_4 and C_5.

Calculate the consistency ratio (C.R)

The value of random indices (*RI*) was retrieved from Saaty (1980). Then the consistency ratio was given by:

$$C.R = \frac{RI\text{-}\frac{\sum \pi_{ij}(x)}{n}}{n\text{-}1} = C.R\ (B_1)\ = \frac{1.12 - \frac{1.8}{5}}{5-1} = 0.1$$

Based on the calculation, the consistency ratio of the aggregated IF judgment matrix for the criteria by B_1 is 0.1. Therefore, the matrix is consistent.

Calculate the IF weight for criteria

The entropy weights for the aggregated IF judgment matrix of criteria are computed by using (9) and (10) As an example, below is the calculation of entropy weights and final weight for C_1 (0.56, 0.03, 0.41).

$$\bar{\bar{w}}_i\text{=-}\frac{1}{5\ln 2}[0.56\ln 0.56\text{+}0.03\ln 0.03\text{-}(1\text{-}0.41)\ln(1\text{-}0.41)\text{-}0.41\ln 2] = 0.1184$$

Then, total sum of all entropy weights,

$$\sum_{j=1}^{n}\bar{\bar{w}}_i\text{=}0.1184\text{+}0.1358\text{+}0.0679\text{+}0.0752\text{+}0.1201\text{=}0.5174$$

Thus, the final entropy weights of each IF matrix is redefined as (13):

$$w_i\text{=}\frac{1\text{-}\bar{\bar{w}}_i}{n\text{-}\sum_{j=1}^{n}\bar{\bar{w}}_i} = \frac{1\text{-}0.1184}{5\text{-}0.5174} = 0.1967$$

Similar calculation was then performed for other criteria to measure the entropy weight and final weight. So, entropy weights and its final weights of aggregated IF judgment matrix criteria by B_1 shows on Table 7.

Table 7. Entropy weights and its final weights of aggregated IF judgement matrix for criteria by B_1

Criteria	Aggregated IF			Entropy weights $\bar{\bar{w}}_i$	Final weights, w_i
C_1	(0.56,	0.03,	0.41)	0.1184	0.1967
C_2	(0.47,	0.04,	0.49)	0.1358	0.1928
C_3	(0.74,	0.01,	0.25)	0.0679	0.2079
C_4	(0.72,	0.02,	0.26)	0.0752	0.2063
C_5	(0.56,	0.04,	0.40)	0.1201	0.1963

UNIFYING PROCESS OF PERFORMANCE MATRIX

The normalization processes are derived based on either cost-benefit criteria which are then naturally represented by each of the criteria. In the quantitative data, C_1 is a benefit and C_2 is a cost. Meanwhile, in the qualitative data, C_3 is a cost and C_4 and C_5 are benefits. Based on that, C_1 is represented by a crisp value and C_2 is represented by an interval figure. The unifying processes are needed to convert them to IFNs based on either the cost or benefit criteria. At this stage, two methods were employed to derive the score values as we mentioned on step 5 in the IF-AHP Procedure. Then, Table 8 shows the IFNs for overall performance by B_1.

Table 8. IFNs for overall performance by B_1

	Effectiveness, C_1	Cost, C_2	Limitation, C_3	Dosage, C_4	Availability, C_5
A_1	(0.44, 0.56, 0.00)	(0.38, 0.39, 0.22)	(0.21, 0.09, 0.70)	(1.00, 0.00, 0.00)	(0.34, 0.26, 0.40)
A_2	(0.36, 0.64, 0.00)	(0.26, 0.58, 0.16)	(0.29, 0.21, 0.50)	(1.00, 0.00, 0.00)	(0.77, 0.13, 0.10)
A_3	(0.47, 0.46, 0.00)	(0.34, 0.46, 0.20)	(0.26, 0.34, 0.40)	(0.21, 0.29, 0.50)	(0.34, 0.26, 0.40)
A_4	(0.46, 0.54, 0.00)	(0.55, 0.23, 0.22)	(0.13, 0.77, 0.10)	(0.77, 0.13, 0.10)	(0.77, 0.13, 0.10)
A_5	(0.50, 0.50, 0.00)	(0.18, 0.73, 0.09)	(0.23, 0.57, 0.20)	(0.34, 0.26, 0.40)	(0.34, 0.26, 0.40)

CONSTRUCT THE DMS AGGREGATE IF JUDGMENT MATRIX

The aggregated IF matrix of criteria was constructed respectively with alternatives using the sequence of decision maker value judgment weights by using (1). The aggregated IF matrix based on weights of the k^{th} GDMs by using (1) and let pairwise comparison for C_1 for all criterion by B_1:

$$\alpha_{ij} = \mathrm{IFWA}_{\beta}\left(\alpha_{ij}^{(1)}, \alpha_{ij}^{(2)}, \ldots, \alpha_{ij}^{(t)}\right)$$
$$= \left(1 - \prod_{k=1}^{t}(1-0.44)^{0.5870}, \prod_{k=1}^{t}(0.56)^{0.5870}, \prod_{k=1}^{t}(1-0.44)^{0.5870} - \prod_{k=1}^{t}(0.56)^{0.5870}\right)$$
$$= (0.29, 0.71, 0.00)$$

CONSTRUCT THE OVERALL AGGREGATE IF JUDGMENT MATRIX BY USING GIFWG OPERATOR

The aggregated IF matrix of criteria was constructed based on alternatives using the sequence of criteria value judgment weights and parameter $\lambda = 0.5$ by using (2) and refer to Table 7 for final weights for every criterion. As an example, below is the calculation for A_1 by $B_1 = (0.32, 0.40, 0.28)$. Then, the similar fashion of calculation is applied to determine overall aggregated IF judgement by all DMs for every alternative. The overall aggregated IF judgment matrix by all DMs is shown in Table 9.

Table 9. The Overall Aggregated IF Judgement Matrix by All DMs

DMs		B_1			B_2			B_3	
Patch, A_1	(0.32,	0.40,	0.28)	(0.18,	0.59,	0.23)	(0.04,	0.93,	0.04)
Gum, A_2	(0.37,	0.47,	0.17)	(0.19,	0.65,	0.16)	(0.03,	0.90,	0.07)
Inhaler, A_3	(0.20,	0.55,	0.25)	(0.14,	0.67,	0.19)	(0.04,	0.93,	0.04)
Lozenge, A_4	(0.32,	0.58,	0.11)	(0.37,	0.53,	0.10)	(0.06,	0.91,	0.03)
Nasal spray, A_5	(0.19,	0.65,	0.16)	(0.18,	0.72,	0.10)	(0.03,	0.94,	0.03)

DEFUZZIFICATION

For each of the DMs, the IF entropy of aggregated was used to compute the overall assessment of alternatives by using (9) and (10). As an example, below is the calculation of entropy weights and final performance for A_1 by B_1 (0.32, 0.40, 0.28).

$$\bar{\bar{w}}_i\text{=-}\frac{1}{5\ln 2}[0.32\ln 0.32\text{+}0.40\ln 0.40\text{-}(1\text{-}0.28)\ln(1\text{-}0.28)\text{-}0.28\ln 2] = 0.1987$$

Then, total sum of all entropy weight

$$\sum_{j=1}^{n}\bar{\bar{w}}_i\text{=}0.1987\text{+}0.1983\text{+}0.1749\text{+}0.1891\text{+}0.1617\text{=}0.9227$$

Thus, the final performance value of each IF matrix is redefined as equation (10):

$$w_i\text{=}\frac{1\text{-}\bar{\bar{w}}_i}{n\text{-}\sum_{j=1}^{n}\bar{\bar{w}}_i} = \frac{1\text{-}0.1987}{5\text{-}0.9227} = 0.1956$$

Similar calculation was then performed for other criteria to measure the entropy weight and final weight.

RANK ALL THE ALTERNATIVES

The relative weights were computed, and alternatives obtained by arithmetic mean of the final performance value were ranked based on alternatives with respect to criteria. Table 10 summarizes the DMs final performance value and rank on the problem alternatives.

Table 10. Final performance value and rank on alternatives NRT selection problem

	Performance value			Final performance value	Rank
	B_1	B_2	B_3		
A_1	0.1965	0.1991	0.2008	0.1988	4
A_2	0.1966	0.2006	0.2002	0.1991	3
A_3	0.2024	0.2046	0.2009	0.2026	2
A_4	0.1989	0.1924	0.1960	0.1958	5
A_5	0.2056	0.2033	0.2021	0.2036	1

In order to arrange the ranking, the bigger value of the final performance value, the greater alternative of the DM selection problem. From the calculation, the best NRT selection problem found is A_5, followed by A_3, A_2, A_1 and A_4. The final performance value is found as $A_5 \succ A_3 \succ A_2 \succ A_1 \succ A_4$ where '$\succ$' means 'preferred or superior to'.

CONCLUSIONS

The construction of the MCDM model was shown to be an efficient tool for dealing with the complexity and ambiguity associated with the NRT as a smoking cessation decision. The study includes a variety of actions aimed at determining the model's practicality. A complete attempt was made to develop useful tools for supporting decision-making in the context of a real-world NRT selection issue, more precisely in the investigated region.

Finally, the use of IFNs in conjunction with AHP for rating purposes is suitable since it facilitates the direct quantification of inaccurate assessment judgments among the DM. It provides a new perspective on an evaluation approach that places a greater emphasis on the consistency of membership grade expressions and the importance of considering the degree of hesitation, as well as a proposed concept that can improve the imprecision of results when compared to the existing approach.

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CONFLICT OF INTEREST

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

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