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An Integrated fuzzy AHP-TOPSIS for the Last Mile Delivery Mode Selection

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ABSTRACT

This paper presents a combined fuzzy Analytic Hierarchy Process (fuzzy AHP) and fuzzy Technique for Order Preference by Similarity to an Ideal Solution (fuzzy TOPSIS) for selecting the last mile delivery modes of online-shopping customers' perspective. There are 8 criteria: office hours, payment options, convenience, product security, delivery cost, environment friendliness, flexibility, direct delivery, and 4 alternatives: attended home delivery, unattended home delivery, manned collection point, and unmanned collection point in this study. There are 1,098 respondents from 23 countries, 3 continents on the online survey. The fuzzy AHP is conducted to quantify the weights to 8 criteria and the fuzzy TOPSIS is conducted to rank 4 delivery modes in line with the weighted criteria. The result shows that customers are quite concerned about product security. This affects selection of attended home delivery mode and manned collection point mode as the first preference and the second preference, respectively. This study also shows that large-group decision making is plausible and is not burdensome on calculation.

Keywords: AHP; Decision science; Last mile delivery; Logistics; Multi-criteria decision making; TOPSIS

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1. Introduction

Last mile delivery (LMD) is a part of logistics that supports the growing e-commerce and is one of the big challenges in e-commerce logistics. Theoretically, LMD is defined as the final delivery procedure of products from distribution centers to destinations and is considered the only connection in the e-commerce logistics that involves direct and face-to-face interaction with customers [1-2]. In e-commerce logistics, LMD is regarded as the most complex and costly task to manage and operate [3].

Moroz and Polkowski [4] pointed out four modes of last mile delivery: home deliveries (attended and unattended) and collection points (manned and unmanned). Gevaers et al. [5] indicated that the post box is also one of the old-fashioned last mile delivery mode. Presently, many companies are developing their innovative LMD; Amazon has employed robots called 'the Scout' in its last mile delivery and DHL has been testing smart drones to meet the needs of customers in an urban area of China. The problem at hand is that LMD relates to all stakeholders in the last-leg logistics and each mode has its advantages and disadvantages with multiple attributes. How do we compare and select the modes that are appropriate to a circumstance of products, sellers, and customers?

This type of problem is in the category of multi-criteria decision making (MCDM) that is an important part of modern decision science [6-7]. MCDM has become a main area of research for dealing with complex decision problems. There are several MCDM methods such as analytic hierarchy process (AHP), technique for order preference by similarity to the ideal solution (TOPSIS), maxi-min (MAXMIN) technique, maxi-max (MAXMAX) technique, simple additive weighting (SAW), simple multi attribute rating technique (SMART), elimination and choice expressing reality (ELECTRE), etc. [8-9]. Among the MCDM methods, AHP and TOPSIS are the most popular in both literature and practices.

We are interested in applying these two methods for solving our problem that is subjective and complicated. An AHP variant, a fuzzy one, will be applied incorporated with a TOPSIS variant, a fuzzy one as well. Many studies have explored the knowledge of fuzzy AHP and fuzzy TOPSIS; however, there is not much literature that applies these two methods simultaneously. This is because of the computational burden when deploying them together. Furthermore, of the myriad literature on small-group decision making (S-GDM), none of them tried to solve the large-group decision making (L-GDM). Accordingly, the gap of this knowledge will be investigated in this study. The main contributions of this paper are the simultaneous application of fuzzy AHP and TOPSIS is systematically proposed and the large-group decision making is presented.

The remainder of this paper is structured as follows: Section 2 draws a short message of previous works that relate to our study. Section 3 briefly describes the fuzzy set theory. Sections 4 and 5 present the traditional methods of AHP and TOPSIS, respectively. In Section 6, the proposed method is briefly described. How the proposed model is used on a real-world example of the last mile delivery mode selection is explained in Section 7. Finally, in Section 8, the conclusion is drawn.

2. Literature Review

In the context of the fuzzy environment, some literature studied the use of the analytic hierarchy process and the technique for order preference by similarity to the ideal solution. In this section, we review the previous works that relate to ours and point out the main differences.

Dagdeviren et al. [10] applied AHP and TOPSIS to solve a multi-criteria decision-making problem in the defense industry. The authors pointed out that their problem is about selecting weapons under the vague, linguistic, and subjective environment. The procedure of the proposed model can be divided into three stages. The first stage is a group working for defining 6 criteria and 5 alternatives. In the second stage, the AHP was applied to find the weight of criteria based on the subjective decision of the expert team. The third stage showed the application of fuzzy TOPSIS to rank the preference. The report, however, did not mention the number of experts in the team and the AHP used was the traditional AHP that was questionable about the fuzzy environment. Nevertheless, the study illustrated the systematic calculation of three stages. It was simple and practical.

Sun [11] pointed out the shortcomings of the traditional AHP. He explained that the AHP method is mainly used in near-crisp data decision making; the AHP makes a very unbalanced scale of judgment; the uncertainty data, linguistic data, and interval-values are not accounted for in the AHP method; and the subjective judgment by perception, evaluation, improvement, selection based on the preference of decision-makers have a great influence on the AHP results. These advantages are in the intention of our study.

Kannan et al. [12] presented a very complicated framework of supplier selection and order allocation in supply chain management. The combination of optimization/decision tools: AHP, TOPSIS, maxi-min method (MAXMIN), and multi-objective linear programming (MOLOP) were deployed. The simulation case of this study is selecting suppliers who comply with green supply chain regulations. The framework worked well in the case study. However, it required much computational work on just 5 criteria and 3 alternatives. Besides, this decision-making was made by only 3 experts. Certainly, the bias and preference of the decision-makers were huge.

Patil & Kant [13] presented a stepwise decision-making framework for ranking knowledge management adoption through the supply chain. The knowledge could not be transferred and shared by supply chain members because of their barriers. This study ordered the significant barriers and then proposed the strategic management for preemptory barriers. The fuzzy AHP was used to determine the weights of the barriers; then, the fuzzy TOPSIS was used to rank the solutions on knowledge management adoption. The proposed method used α-cut method to rank the fuzzy numbers. In their study, a panel of 15 experts was used in the case of a hydraulic valve manufacturer who needed to select the suppliers that conformed to its strategies. The calculation method is skeptical in the case of a large-size expert panel, say three digits.

Kusumawardani and Agintiara [14] deployed the fuzzy AHP-TOPSIS method to solve the problem of human resource manager selection in a telecommunication company. The fuzzy AHP was used to weigh 10 performance assessment criteria. Some of them were crisp data while some of them were linguistic data. The fuzzy TOPSIS ranks the candidates based on their best non-fuzzy performance (BNP). The decision-making process in the case study used five HR managers as the expert panel.

Up to this point, it is not new for applying the fuzzy AHP and fuzzy TOPSIS in multi-criteria decision making. However, to the best of our knowledge, all of the previous works were based on a small-group of experts because of the computational burden. Thus, in our study, we will explore the integrated fuzzy AHP-TOPSIS in the situation of the large-group decision making (L-GDM) whilst considering the cumbersome calculation.

3. Fuzzy Set Theory

A fuzzy set can be defined as a class of objects, with a continuum of membership grades, where the membership grade can be taken as an intermediate value between 0 and 1 [15]. Fundamentally, two main definitions need to be clarified: a fuzzy set and the concept of fuzzy numbers.

Definition 3.1. (*Fuzzy set*). Let X be a universe of discourse. Where $\tilde{A}$ is a fuzzy subset of X; and $\forall x \in X$, there is a number $\mu_{\tilde{A}}(x) \in [0,1]$ which is assigned to represent the membership of x in $\tilde{A}$, and is called the membership of $\tilde{A}$ [16].

Definition 3.2. (*Fuzzy number*). A fuzzy number $\tilde{A}$ is a normal and convex fuzzy subset of X. Here, "normality" implies that: $\exists x \in R, \vee_x \mu_{\tilde{A}}(x) = 1$ and convex means that $\forall x_1, x_2 \in X, \forall \alpha \in [0,1]$, $\mu_{\tilde{A}}(\alpha x_1 + (1-\alpha)x_2) \geq \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2))$.

In fuzzy set theory, an uncertain situation can be modeled by using different types of membership functions such as triangular, trapezoidal, Gaussian, sigmoid, etc. Nevertheless, it has been found that the triangular membership function is simple and easy to use whilst providing a better solution for solving problems with imprecise data [17-18].

Definition 3.3. A triangular fuzzy number $\tilde{A}$ can be defined by a triplet (a,b,c) as shown in Fig.1.

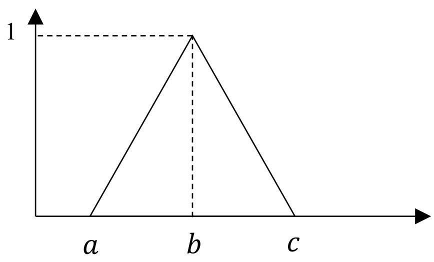

Fig.1. Triangular membership function.

The membership function of a triangular fuzzy number can be defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a, \\ \dfrac{x-a}{b-a}. & a \leq x \leq b, \\ \dfrac{c-x}{c-b} & b \leq x \leq c, \\ 0, & x > c, \end{cases} \tag{3.1}$$

where a, b, and c are real numbers with the following order and priority $a < b < c$. They can be referred to as lower, middle, and upper possible values [15]. It is worth noting that the first and the fourth conditions in Eq. (3.1) represent the fact that outside the defined domain [0,1] the degree of pertinence is zero.

The arithmetic operations of two triangular fuzzy numbers and a real number can be defined as follow:

$$\tilde{A} \oplus \tilde{B} = (a_1 + a_2, b_1 + b_2, c_1 + c_2), \tag{3.2}$$

$$\tilde{A} \ominus \tilde{B} = (a_1 - a_2, b_1 - b_2, c_1 - c_2), \tag{3.3}$$

$$\tilde{A} \otimes \tilde{B} = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2), \tag{3.4}$$

$$\tilde{A} \varnothing \tilde{B} = (a_1 \div a_2, b_1 \div b_2, c_1 \div c_2), \tag{3.5}$$

$$k\tilde{A} = (k \times a_1, k \times b_1, k \times c_1), \tag{3.6}$$

where $\tilde{A} = (a_1, b_1, c_1), \tilde{B} = (a_2, b_2, c_2), k =$ a real number. Furthermore, the distance between two fuzzy numbers can be calculated as follows:

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}\left[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2\right]}. \tag{3.7}$$

4. Traditional AHP

The Analytic Hierarchy Process (AHP) method was developed by Saaty [19]. It is a powerful method to solve complex decision problems. The problem can be decomposed into several sub-problems using AHP in terms of hierarchical levels where each level represents a set of criteria or attributes relative to each sub-problem. This method is based on three principles: first, the structure of the model; second, the comparative judgment of the alternatives and the criteria; third, the synthesis of the priorities. The steps of the AHP method can be described as follows:

Step 1: A set of criteria is defined as $C = \{C_j \mid j = 1,2,3,...,n\}$. This set is initially broken down from a complex multi-criteria decision-making problem. AHP arranges the objectives, criteria, and alternatives into a hierarchical structure the same as a family tree.

Step 2: The pairwise comparisons of the criteria. The number of criteria pairwise comparisons can be determined by using the formula $\frac{n^2 - n}{2}$, where n is the number of criteria in the consideration. Eq. (4.1) represents the matrix of pairwise comparison.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix}, a_{jj} = 1, a_{ij} = \frac{1}{a_{ji}}. \quad (4.1)$$

Step 3: The relative weights of criteria are calculated. They are given by the right eigenvector (w) corresponding to the largest eigenvalue $(\lambda_{\max})$ as,

$$Aw = \lambda_{\max} w. \quad (4.2)$$

Step 4: The consistency of the comparison matrix is checked. Consistency is an important factor in AHP. For checking the consistency of the comparison matrix, a consistency index (*CI*) is calculated as,

$$CI = \frac{\lambda_{\max} - n}{n - 1}. \quad (4.3)$$

Then, the consistency ratio (*CR*) is calculated for concluding whether the evaluations are sufficiently consistent. The *CR* can be determined by taking the ratio of the *CI* and the random index (*RI*), suggested by Saaty [20].

$$CR = \frac{CI}{RI}. \quad (4.4)$$

The *CR* should not exceed 0.1. If its value exceeds 0.1, then it is suggested that the comparison process is not consistent, it should be carried out again to improve the consistency. Table 1 shows the standard nine-point comparison scale.

Table 1. Nine-point comparison scale.

Definition	Intensity of important
Equally important	1
Moderately more important	3
Strongly more important	5
Very strongly more important	7
Extremely more important	9
Intermediate values	2, 4, 6, 8

5. Traditional TOPSIS

The technique for order performance by similarity to ideal solution (TOPSIS) was developed by Hwang & Yoon in 1981 [21]. Technically, the best alternative would be the one that is nearest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS) [8]. TOPSIS considers the distances of both PIS and NIS at the same time. The traditional TOPSIS method was innovated for a single decision making. It could not determine the preference for group decision-making. Thus, Shih et al. (2007) [22] extended the ability of TOPSIS by making a variant TOPSIS for group decision making. We will review the procedure of this variant in this section proposed by Shih et al. (2007). Suppose there are k decision-makers in a set K. The procedure is described as follows.

Step 1: Construct the decision matrix $D^k, \forall k \in K$.

$$D^k = \begin{matrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} x_{11}^k & \cdots & x_{1j}^k & \cdots & x_{1n}^k \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1}^k & \cdots & x_{ij}^k & \cdots & x_{in}^k \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1}^k & \cdots & x_{mj}^k & \cdots & x_{mn}^k \end{bmatrix}, \quad (5.1)$$
$$\quad X_1 \quad \cdots \quad X_j \quad \cdots \quad X_n$$

where A_i denotes the alternative i, $i = 1,...,m;$ X_j denotes the attribute or criterion j, $j = 1,...,n;$ with quantitative and qualitative data. x_{ij}^k is the performance rating of the alternative A_i with respect to attribute X_j by decision-maker k, $k \in K$. It is noted that there are K decision matrices for the K members of the group.

Step 2: Calculate the normalized decision matrix. This step transforms different dimensions into non-dimensional attributes that allow us to compare them across criteria. There are many normalization techniques but the most common in literature is vector normalization as shown in Eq. (5.2).

$$r_{ij}^k = \frac{x_{ij}^k}{\sqrt{\sum_{j=1}^{n}\left(x_{ij}^k\right)^2}}, \quad (5.2)$$

where $i = 1,...,m; j = 1,...,n;$ and $k \in K.$

Step 3: Determine PIS and NIS for each decision-maker $k, \forall k \in K$. The PIS V^{k+} for k-decision maker is in Eq. (5.3) and the NIS V^{k-} for k-decision maker is in Eq. (5.4).

$$V^{k+} = \left\{r_1^{k+},...,r_n^{k+}\right\}$$
$$= \left\{\left(\max_i r_{ij}^k \mid j \in J\right), \left(\min_i r_{ij}^k \mid j \in J'\right)\right\}, \quad (5.3)$$

$$V^{k-} = \left\{r_1^{k-},...,r_n^{k-}\right\}$$
$$= \left\{\left(\min_i r_{ij}^k \mid j \in J\right), \left(\max_i r_{ij}^k \mid j \in J'\right)\right\}, \quad (5.4)$$

where J is J associated with the benefit criteria and is associated with the cost criteria.

Step 4: Assign a weight vector W for each decision-maker in the group. Let w_j^k be the weight for attribute j where $j = 1,...,n$ and for k-decision maker. It is worth noting that $\sum_{j=1}^{n} w_j^k = 1$.

Step 5a: Calculate the separation measure for individuals. The separation of i^{th} alternative A_i from the PIS, V^{k+} ,for each k-decision maker is given as

$$d_i^{k+} = \left\{\sum_{j=1}^{m} w_j^k \left(r_{ij}^k - r_j^{k+}\right)\right\}^{1/p}. \quad (5.5)$$

The separation of i^{th} alternative A_i from the NIS, V^{k-} , for each k- decision maker is given as

$$d_i^{k-} = \left\{\sum_{j=1}^{m} w_j^k \left(r_{ij}^k - r_j^{k-}\right)\right\}^{1/p}, \quad (5.6)$$

where $i = 1,...,m$ and $p \geq 1$. For $p = 2$ the Euclidean metric is used.

Step 5b: Calculate the separation measure for the group. The assembled separation measures of the positive ideal d_i^{*+} and the negative ideal d_i^{*-} for alternative A_i are given by one of the operators, arithmetic mean and geometric mean.

$$d_i^{*+} = \frac{\sum_{k=1}^{K} d_i^{k+}}{K} \text{ and } d_i^{*-} = \frac{\sum_{k=1}^{K} d_i^{k-}}{K}, \quad (5.7)$$

$$d_i^{*+} = \sqrt[k]{\prod_{k=1}^{K} d_i^{k+}} \text{ and } d_i^{*-} = \sqrt[k]{\prod_{k=1}^{K} d_i^{k-}}. \quad (5.8)$$

Step 6: Calculate the relative closeness to the positive ideal solution for the group. It can be calculated by using Eq. (5.9).

$$RCC_i^* = \frac{d_i^{*-}}{d_i^{*-} + d_i^{*+}}, i = 1,...,m. \quad (5.9)$$

6. Integrated fuzzy AHP-TOPSIS

The traditional AHP and TOPSIS methods are based on personal judgments that are represented with crisp values. However, in real life, the crisp values may not be suitable and make the respondents reluctant. Thus, linguistic values may be a better approach. This brings us to consider the fuzzy technique and fuzzy set theory. In this section, the fuzzy AHP and the fuzzy TOPSIS are briefly described. Then, the integrated method will be proposed.

6.1 The fuzzy AHP

The limitations of the traditional AHP are 1) the traditional AHP is used in crisp decision making; 2) it creates the very unbalanced scale of judgment; 3) it cannot handle uncertainty and ambiguous data; 4) the ranking of the traditional AHP method is imprecise; 5) the traditional AHP results may be greatly influenced by the subjective judgment, selection, and preference of decision-makers [23].

Accordingly, the fuzzy AHP method is the extended version that incorporates fuzzy set theory to solve hierarchical fuzzy problems. The modified method can deal with the uncertain imprecise judgment of decision- makers who make linguistic variables. Moreover, our proposed method includes the characteristics of large-group decision making (L-GDM) which was modified from Patil & Kent (2014) [13] and Zyoud et al. (2016) [23]. The steps of the fuzzy AHP are as follows:

Step 1: Translate the linguistic terms used by DMs to express the comparative judgments among the main criteria concerning the overall goal. The evaluation concerning the main criterion will be numbered in triangular fuzzy numbers (TFNs) as shown in Eq. (6.1).

$$\tilde{A}=\begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix}, \qquad (6.1)$$

where $\tilde{a}_{ij}=1$, if criterion i equals to criterion j and $\tilde{a}_{ij}=\left(\tilde{1},\tilde{3},\tilde{5},\tilde{7},\tilde{9}\right)$ if criterion i is not equal to criterion j.

The range of values used in TFNs are shown as the scales in Table 2 and its graph of membership function is shown in Fig.2.

Table 2. The scale of linguistic evaluation.

Fuzzy Number	Linguistic	TFNs (l,m,u)	Reciprocal TFNs
$\tilde{1}$	Equally important	(1, 1, 1)	(1, 1, 1)
$\tilde{3}$	Moderately more important	(1, 3, 5)	(1/5,1/3,1)
$\tilde{5}$	Strongly more important	(3, 5, 7)	(1/7,1/5,1/3)
$\tilde{7}$	Very strongly more important	(5, 7, 9)	(1/9,1/7,1/5)
$\tilde{9}$	Extremely more important	(7, 9, 9)	(1/9,1/9,1/7)

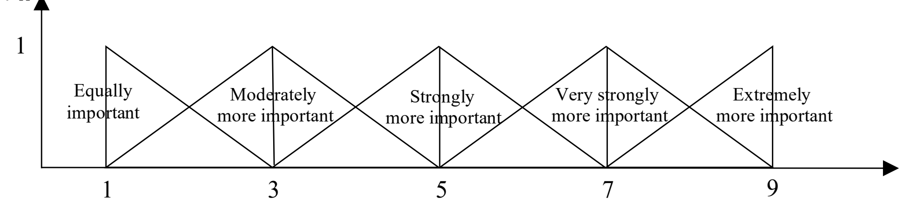

Fig.2. Membership function of linguistics variables.

Step 2: By using geometric mean technique to define the fuzzy geometric mean and fuzzy weights of each criterion, Eq. (6.2) and Eq. (6.3) are deployed [24]:

$$\tilde{r}_i=\left(\tilde{a}_{i1}\otimes\tilde{a}_{i2}\otimes\cdots\otimes\tilde{a}_{in}\right)^{1/n}, \qquad (6.2)$$

$$\tilde{w}_i=\tilde{r}_1\otimes\left(\tilde{r}_1\oplus\tilde{r}_2\oplus\cdots\oplus\tilde{r}_n\right)^{-1}, \qquad (6.3)$$

where $\tilde{a}_{in}$ is fuzzy comparison value of criterion i to criterion n, thus, $\tilde{r}_i$ is the geometric mean of fuzzy comparison value of criterion i to each criterion, $\tilde{w}_i$ is the triangular fuzzy weight of the i^{th} criterion, in which $\tilde{w}_i = (Lw_i, Mw_i, Uw_i)$. Therefore, Lw_i, Mw_i, and Uw_i stand for the lower, middle, and upper values of the fuzzy weight of the ith criterion.

Step 3: Aggregate the preference of k DMs for building the final pairwise comparison matrix. We need to cope with L-GDM. To do so, a calculation method should be deployed. There are three recommended methods as shown below.

Method A: Weight aggregation 1 [25].

$$Lw_i = \min_k \{Lw_i^k\},$$
$$Mw_i = \frac{1}{k}\sum_{k=1}^{K} Mw_i^k, \tag{6.4}$$
$$Uw_i = \max_k \{Uw_i^k\},$$

where $\tilde{w}_i$ is the triangular fuzzy weight of the ith criterion in comparison with the j^{th} criterion.

Method B: Weight aggregation 2. It is based on arithmetic operations.

$$Lw_i = \frac{1}{K}\sum_{k=1}^{K} Lw_i ,$$
$$Mw_i = \frac{1}{K}\sum_{k=1}^{K} Mw_i , \tag{6.5}$$
$$Uw_i = \frac{1}{K}\sum_{k=1}^{K} Uw_i .$$

Method C: Weight aggregation 3. It is based on the geometric mean of preferences.

$$Lw_i = \left(\prod_{k=1}^{K} Lw_i\right)^{1/2},$$
$$Mw_i = \left(\prod_{k=1}^{K} Mw_i\right)^{1/2}, \tag{6.6}$$
$$Uw_i = \left(\prod_{k=1}^{K} Uw_i\right)^{1/2}.$$

Please note that, in this study, we make use of the weight aggregation 1 because it had been proved that this method leads to less distortion of the weight among the three methods [23].

6.2 The fuzzy TOPSIS

The fuzzy TOPSIS technique was first proposed by Chen (2000) [26] for solving multi-criteria decision making problems with the fuzzy environment and uncertainty evaluations. The technique evaluates alternatives with respect to a set of criteria and as the linguistic decision makers' opinions are subjective, vague, and imprecise [27]. Accordingly, the fuzzy set theory must be used, and TFNs shall be used to define the linguistic decision makers' opinions as shown in Table 3.

Table 3. Definition of linguistic evaluation.

Fuzzy Number	Linguistic	TFNs (l, m, u)
$\tilde{1}$	Very poor	(1, 1, 1)
$\tilde{3}$	Poor	(1, 3, 5)
$\tilde{5}$	Fair	(3, 5, 7)
$\tilde{7}$	Good	(5, 7, 9)
$\tilde{9}$	Very good	(7, 9, 9)

This section describes the extended TOPSIS in the fuzzy environment. It is particularly suitable for solving the group decision- making problem under a fuzzy environment. The mathematics technique is based on [28-29] and [23]. The steps of fuzzy TOPSIS can be described as follows:

Step 1: Assign rating values for the linguistic variables with respect to criteria using the scale as shown in Table 3. Then, the matrices for alternatives in the fuzzy form are constructed.

$$\tilde{D} = \begin{matrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix}, \tag{6.7}$$
$$\quad C_1 \quad \cdots \quad C_j \quad \cdots \quad C_n$$

$$\tilde{x}_{ij} = \frac{1}{k}\left(\tilde{x}_{ij}^{1} \oplus \cdots \oplus \tilde{x}_{ij}^{k}\right), \tag{6.8}$$

where $\tilde{x}_{ij}^{k}$ is the performance rating of alternative A_i with respect to criterion C_j evaluated by kth decision-maker, and $\tilde{x}_{ij}^{k} = \left(l_{ij}^{k}, m_{ij}^{k}, u_{ij}^{k}\right)$.

Step 2: Normalize the fuzzy-decision matrix which is denoted by $\tilde{R}$ as shown in Eq. (6.9).

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n}, \tag{6.9}$$

where $i = 1,...,m,$ and $j = 1,2,...,n.$

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^{+}}, \frac{m_{ij}}{u_j^{+}}, \frac{u_{ij}}{u_j^{+}}\right), \tag{6.10}$$

where $u_j^{+} = \max_i \left\{u_{ij} \mid i = 1,2,...,n\right\}$.

The weighted fuzzy normalized decision matrix is shown as the following:

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n}, \tag{6.11}$$

where $i = 1,...,m, j = 1,2,...,n,$ and $\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j$.

Step 4: Calculate the fuzzy positive-ideal solution (f-PIS) and fuzzy negative-ideal solution (f-NIS). The elements $\tilde{v}_{ij}$ are normalized positive TFN and their ranges belong to the closed interval [0,1]. The f-PIS A^{+} and f-NIS A^{-} as the following equations:

$$A^{+} = \left(\tilde{v}_1^{*},...,\tilde{v}_j^{*},...,\tilde{v}_n^{*}\right) = \left\{\max_i \tilde{v}_{ij} \mid \left(i = 1,2,...,n\right)\right\}, \tag{6.12}$$

$$A^{-} = \left(\tilde{v}_1^{-},...,\tilde{v}_j^{-},...,\tilde{v}_n^{-}\right) = \left\{\min_i \tilde{v}_{ij} \mid \left(i = 1,2,...,n\right)\right\}, \tag{6.13}$$

Step 5: Calculate the distance of each alternative between A^{+} and A^{-}.

$$d_i^{+} = \left\{\frac{1}{3}\sum\nolimits_{j=1}^{n}\left(\tilde{v}_{ij} - \tilde{v}_j^{*}\right)^2\right\}^{1/2}, \tag{6.14}$$

$$d_i^{-} = \left\{\frac{1}{3}\sum\nolimits_{j=1}^{n}\left(\tilde{v}_{ij} - \tilde{v}_j^{-}\right)^2\right\}^{1/2}, \tag{6.15}$$

Step 6: Calculate the relative closeness coefficient $\left(\tilde{R}_i^{*}\right)$ of each alternative.

$$RCC_i^{*} = \frac{\tilde{d}_i^{-}}{\tilde{d}_i^{-} + \tilde{d}_i^{+}}, i = 1,...,m, \tag{6.16}$$

where $RCC_i^{*} \in \left(0,1\right)$.

Step 7: Rank the alternatives as per relative closeness by using RCC_i^{*} in descending order.

6.3 The integration procedure

As mentioned earlier, the proposed method is customized to cope with fuzzy environments and L-GDM. A combined approach of fuzzy AHP and fuzzy TOPSIS method is used to handle the complex problems. Precisely, the fuzzy AHP is used to calculate the weights of different criteria and fuzzy TOPSIS is used to rank the alternatives. Fig.3 illustrates the phases of the procedure and the details are described as follows:

Phase I: Identify alternatives, criteria, and sub-criteria. In this step, a group of experts may be needed to identify all relevant factors and the goals of the problem. However, a practitioner may conduct preliminary survey research to collect some important data from the target (such as customers).

Phase II: Computation of the weights of the criteria. In this phase, the fuzzy AHP is employed. The difficulty is that each comparison matrix corresponds to only one decision-maker. Accordingly, for a large-decision maker group, we do have k-pairwise comparison matrices. The method of Eq. (6.4) is employed to solve the aggregate weight. Technically, a spreadsheet could be used to calculate this without difficulty.

Phase III: Evaluation of the solutions and determine final rank by fuzzy TOPSIS. The group of decision-makers was asked to construct a fuzzy evaluation matrix by using linguistic variables shown in Table 3. The matrices are established by comparing alternatives under each of the criteria separately. Likewise, we obtained k-comparison matrices that would be aggregated by using Eq. (6.8). Then, the procedure to find f-PIS and f-NIS until ranking the alternatives are to follow steps 2 to 6 in Section 6.2.

7. LMD Mode Selection

As mentioned earlier, the selection of last mile delivery modes is very complex. It can be formulated as a multi-criteria decision analysis. We made use of fuzzy AHP-TOPSIS to solve this problem systematically. Please noted that the way of regarding the mode selection in this paper is from the customers' perspective.

7.1 Decision criteria identification

Criteria to be considered in the selection of last mile delivery modes were determined by a group of customers who placed an order on online shopping at least one order in the last month. These eight criteria are as follows: office hours (C_1), payment options (C_2), convenience (C_3), product security (C_4), delivery cost (C_5), environment friendly (C_6), flexibility (C_7), direct delivery (C_8). As a result, only these eight criteria were used in the evaluation and the decision hierarchy was established accordingly (see Table 4).

7.2 Alternatives of LMD modes

The alternatives of last mile delivery mode were selected from the practical operations in the real-world of the delivery service industry. There are four choices: attended home delivery (A_1), unattended home delivery (A_2), manned collection point (A_3), and unmanned collection point (A_4). The description of the modes is given in Table 4 and Fig. 4 shows the hierarchy structure.

7.3 Weight of criteria evaluation

An internet survey was conducted in 23 countries, 3 continents. There are 1,098 respondents in this study. As a result, there are 1,098 matrices. The example of a fuzzy decision matrix is shown in Table 5.

Table 4. Criteria and alternative LMD selection.

Criteria	Definition
C_1	The opening hours of the service point is suitable for customers picking up goods.
C_2	Varieties of payment options; pay directly at the counter, cash on delivery, pay by credit card, etc.
C_3	High convenience for recipients in terms of delivery service.
C_4	Parcels are safe, unbroken, undamaged, trackable, not lost.
C_5	Low delivery cost.
C_6	The delivery process emits less pollution, noise, and traffic congestion.
C_7	Delivery time is set to be of benefit for the customer; ultimately, the customer can choose the delivery time.
C_8	Goods are delivered to the recipients' front door.
Alternatives	Definition
A_1	The service provider sends to recipient's hand at his/her front door.
A_2	The parcel is dropped at the recipient's front door.
A_3	There are collection points that the recipient can collect with face-to-face service.
A_4	There are collection points that the recipient can collect without face-to-face service.

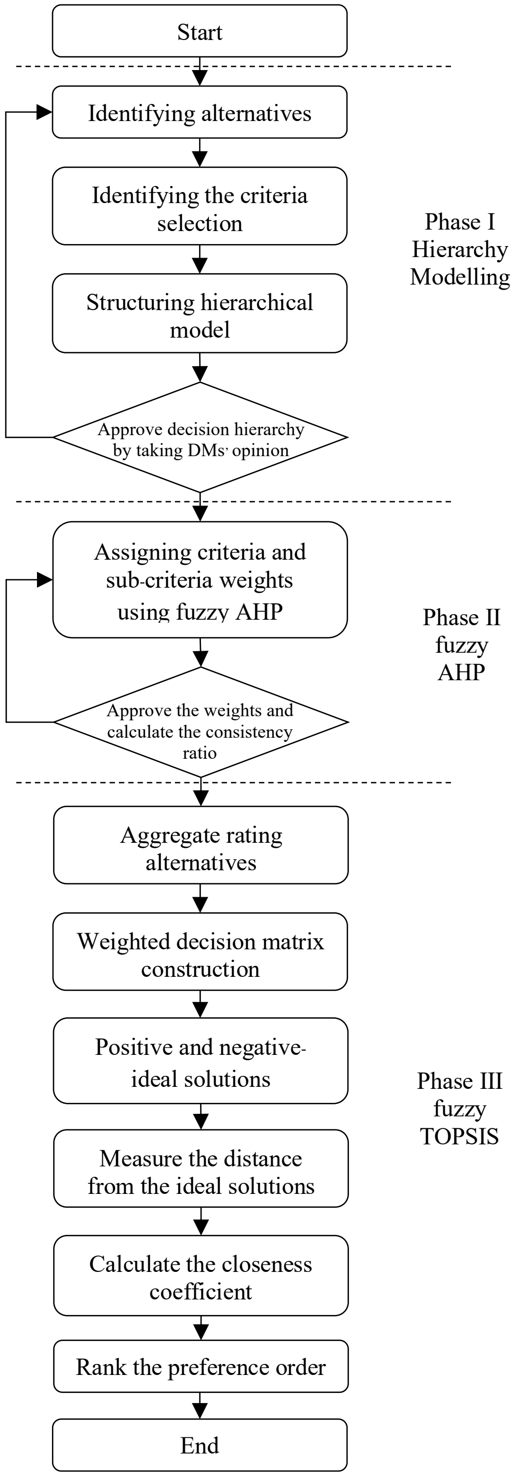

Fig. 3. Proposed procedure of the integrated fuzzy AHP-TOPSIS.

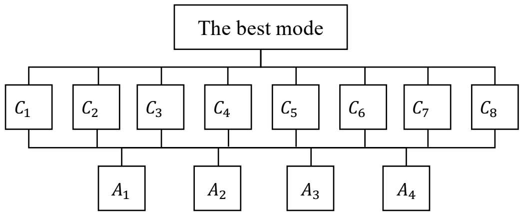

Fig. 4. The decision hierarchy of mode selection.

Each matrix can be used to calculate the fuzzy geometric mean and then the fuzzy weights of each criterion by using Eq. (6.2) and Eq. (6.3), respectively. From Table 5, the example of $\tilde{r}_1$ calculation is shown below.

$$\tilde{r}_1 = \left(1\times\frac{1}{5}\times\frac{1}{7}\times\frac{1}{9}\times1\times1\times\frac{1}{5}\times\frac{1}{9}\right)^{\frac{1}{8}},$$

$$\left(1\times\frac{1}{3}\times\frac{1}{5}\times\frac{1}{7}\times3\times1\times\frac{1}{3}\times\frac{1}{7}\right)^{\frac{1}{8}},$$

$$\left(1\times1\times\frac{1}{3}\times\frac{1}{5}\times5\times1\times1\times\frac{1}{5}\right)^{\frac{1}{8}},$$

$$=\left(0.30,0.44,0.71\right).$$

The values of $\tilde{r}_i$ for $i=1,...,8$ of the example matrix in Table 5 are shown in Table 6. Please note that there are 1,098 matrices from 1,098 respondents, thus, there are 1,098 means ($\tilde{r}_i$) and weights ($\tilde{w}_i$) of each criterion. We deployed Eq. (6.4) to calculate the weight aggregation: Lw_i, Mw_i, and Uw_i for $i=1,...,8$. The result is shown in Table 7.

Table 5. Fuzzy decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	(1 ,1 ,1)	(1/5,1/3,1)	(1/7,1/5,1/3)	(1/9,1/7,1/5)	(1, 3, 5)	(1, 1, 1)	(1/5,1/3,1)	(1/9,1/7,1/5)
C_2	(1, 3, 5)	(1 ,1 ,1)	(1, 1, 1)	(1/7,1/5,1/3)	(5, 7, 9)	(1, 3, 5)	(1, 3, 5)	(1/7,1/5,1/3)
C_3	(3, 5, 7)	(1, 1, 1)	(1 ,1 ,1)	(1/7,1/5,1/3)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(1/5,1/3,1)
C_4	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1 ,1 ,1)	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(1, 1, 1)
C_5	(1/5,1/3,1)	(1/9,1/7,1/5)	(1/9,1/7,1/5)	(1/9,1/9,1/7)	(1 ,1 ,1)	(5, 7, 9)	(1/5,1/3,1)	(1/9,1/9,1/7)
C_6	(1, 1, 1)	(1/5,1/3,1)	(1/7,1/5,1/3)	(1/9,1/7,1/5)	(1/9,1/7,1/5)	(1 ,1 ,1)	(1/5,1/3,1)	(1/7,1/5,1/3)
C_7	(1, 3, 5)	(1/5,1/3,1)	(1/5,1/3,1)	(1/9,1/7,1/5)	(5, 7, 9)	(1, 3, 5)	(1 ,1 ,1)	(1/7,1/5,1/3)
C_8	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(1, 1, 1)	(7, 9, 9)	(3, 5, 7)	(3, 5, 7)	(1 ,1 ,1)

Table 6. Means and weights of criteria.

Criteria	$\tilde{r}_i$	$\tilde{w}_i$
C_1	(0.30, 0.44,0.71)	(0.03,0.03,0.04)
C_2	(0.75, 1.29,1.83)	(0.08,0.09,0.11)
C_3	(1.03,1.56,2.28)	(0.12,0.12,0.14)
C_4	(3.07,4.08,4.88)	(0.30,0.36,0.36)
C_5	(0.27,0.34,0.54)	(0.03,0.03,0.03)
C_6	(0.24,0.31,0.51)	(0.02,0.03,0.08)
C_7	(0.49,0.82,1.40)	(0.06,0.06,0.08)
C_8	(2.35,3.52,4.39)	(0.27,0.27,0.27)

Table 7. Aggregated weights of criteria

Criteria	Lw_i	Mw_i	Uw_i
C_1	0.01	0.03	0.09
C_2	0.12	0.12	0.13
C_3	0.12	0.13	0.21
C_4	0.25	0.37	0.42
C_5	0.01	0.02	0.03
C_6	0.02	0.04	0.10
C_7	0.05	0.07	0.11
C_8	0.22	0.29	0.35

7.4 Evaluation of alternatives

We then executed the TOPSIS analysis. Table 8 is an example of a respondent's rating.

We then calculated aggregated rating of 1,098 respondents ($\tilde{D}$) by using Eq. (6.8). The result is shown in Table 9. The normalization of the aggregated rating values matrix, $\tilde{R}$, was calculated by using Eq. (6.10). $\tilde{R}$ is shown in Table 10.

The next step is the calculation of the weighted fuzzy-normalized decision matrix by using Eq. (6.11). Please note that the weights are based on the aggregated weights of criteria, Table 7. The weighted fuzzy-normalized decision matrix ($\tilde{V}$) is shown in Table11.

From Table 11, we can list the fuzzy positive-ideal solution (f-PIS) and the fuzzy-ideal negative solution (f-NIS) as shown in Table 12.

Table 8. Rating values with respect to criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(1, 1, 1)	(1, 3, 5)	(7, 9, 9)
A_2	(1, 3, 5)	(1, 1, 1)	(3, 5, 7)	(1, 1, 1)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(3, 5, 7)
A_3	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)
A_4	(3, 5, 7)	(1, 3, 5)	(1, 1, 1)	(1, 1, 1)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(1, 1, 1)

Table 9. Aggregated rating values with respect to criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(4.38,6.38,8.12)	(4.54,6.54,8.54)	(4.58,6.58,7.94)	(4.00,6.00,7.70)	(3.22,5.22,7.14)	(2.02,3.22,4.41)	(2.00,3.50,5.00)	(4.64,6.52,7.42)
A_2	(2.90,4.78,6.12)	(2.20,3.70,4.84)	(2.60,4.12,5.36)	(1.78,2.94,4.08)	(2.42,4.06,5.68)	(1.82,3.54,5.24)	(3.66,5.66,7.66)	(3.68,5.66,7.64)
A_3	(4.26,6.24,7.92)	(4.38,6.36,8.14)	(4.34,6.34,8.14)	(4.02,6.00,7.78)	(3.66,5.64,7.60)	(4.02,5.64,7.60)	(3.90,5.28,7.00)	(2.84,4.52,6.26)
A_4	(3.44,5.40,7.32)	(2.10,3.62,5.10)	(1.74,3.08,4.38)	(1.70,3.04,4.34)	(3.72,5.46,7.20)	(4.52,6.50,8.48)	(5.68,6.80,8.78)	(2.16,3.36,4.56)

Table 10. Normalized fuzzy-decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.54,0.79,1.00)	(0.53,0.77,1.00)	(0.56,0.81,0.98)	(0.51,0.77,0.99)	(0.42,0.69,0.94)	(0.24,0.38,0.52)	(0.23,0.40,0.57)	(0.61,0.85,0.97)
A_2	(0.36,0.59,0.75)	(0.26,0.43,0.57)	(0.32,0.51,0.66)	(0.23,0.38,0.52)	(0.32,0.53,0.75)	(0.21,0.42,0.62)	(0.42,0.64,0.87)	(0.48,0.74,1.00)
A_3	(0.52,0.44,0.98)	(0.51,0.74,0.95)	(0.53,0.78,1.00)	(0.52,0.77,1.00)	(0.48,0.74,1.00)	(0.47,0.67,0.90)	(0.44,0.60,0.80)	(0.37,0.59,0.82)
A_4	(0.42,0.67,0.90)	(0.25,0.42,0.60)	(0.21,0.38,0.54)	(0.22,0.39,0.56)	(0.49,0.72,0.95)	(0.53,0.77,1.00)	(0.65,0.77,1.00)	(0.28,0.44,0.60

Table 11. Weighted fuzzy-normalized decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.005,0.024,0.090)	(0.064,0.092,0.130)	(0.068,0.105,0.205)	(0.129,0.285,0.416)	(0.004,0.014,0.028)	(0.005,0.015,0.052)	(0.011,0.028,0.063)	(0.134,0.247,0.340)
A_2	(0.004,0.018,0.068)	(0.031,0.052,0.074)	(0.038,0.066,0.138)	(0.057,0.140,0.220)	(0.003,0.011,0.022)	(0.004,0.017,0.062)	(0.021,0.045,0.096)	(0.106,0.215,0.350)
A_3	(0.005,0.023,0.088)	(0.062,0.089,0.124)	(0.064,0.101,0.210)	(0.129,0.285,0.420)	(0.005,0.015,0.030)	(0.009,0.027,0.090)	(0.022,0.042,0.088)	(0.082,0.172,0.287)
A_4	(0.004,0.020,0.081)	(0.030,0.051,0.078)	(0.026,0.049,0.113)	(0.055,0.145,0.234)	(0.005,0.014,0.028)	(0.011,0.031,0.100)	(0.032,0.054,0.110)	(0.062,0.128,0.209)

Table 12. The f-PIS and f-NIS.

	A^+	A^-
C_1	0.090	0.004
C_2	0.130	0.030
C_3	0.210	0.026
C_4	0.420	0.055
C_5	0.030	0.003
C_6	0.100	0.004
C_7	0.110	0.011
C_8	0.350	0.062

7.5 Ranking of alternatives

The distances of alternatives are calculated. The example of the calculation of alternative 1 is shown below. For the positive distance,

$$d_i^+ = \sqrt{\frac{1}{3}\left((0.005-0.090)^2+(0.024-0.090)^2+(0.090-0.090)^2\right)}$$
$$+\sqrt{\frac{1}{3}\left((0.061-0.130)^2+(0.092-0.130)^2+(0.130-0.130)^2\right)}$$
$$\vdots$$
$$+\sqrt{\frac{1}{3}\left((0.011-0.110)^2+(0.028-0.110)^2+(0.063-0.110)^2\right)}$$
$$+\sqrt{\frac{1}{3}\left((0.134-0.350)^2+(0.247-0.350)^2+(0.340-0.350)^2\right)}$$
$$=0.707.$$

For the negative distance,

$$d_i^- = \sqrt{\frac{1}{3}\left((0.005-0.004)^2+(0.024-0.004)^2+(0.090-0.004)^2\right)}$$
$$+\sqrt{\frac{1}{3}\left((0.061-0.030)^2+(0.092-0.030)^2+(0.130-0.030)^2\right)}$$
$$\vdots$$
$$+\sqrt{\frac{1}{3}\left((0.011-0.110)^2+(0.028-0.110)^2+(0.063-0.110)^2\right)}$$
$$+\sqrt{\frac{1}{3}\left((0.134-0.062)^2+(0.247-0.062)^2+(0.340-0.062)^2\right)}$$
$$=0.761.$$

We then calculate the relative closeness coefficient (RCC_i) of the alternatives. The example of RCC_1 calculation is shown below and all fuzzy TOPSIS results are shown in Table 13.

$$RCC_1 = \frac{0.761}{0.707+0.761} = 0.518.$$

Table 13. Fuzzy TOPSIS results.

	d_i^+	d_i^-	RCC_i	Rank
A_1	0.707	0.761	0.518	1
A_2	0.892	0.532	0.374	3
A_3	0.738	0.748	0.503	2
A_4	0.944	0.474	0.334	4

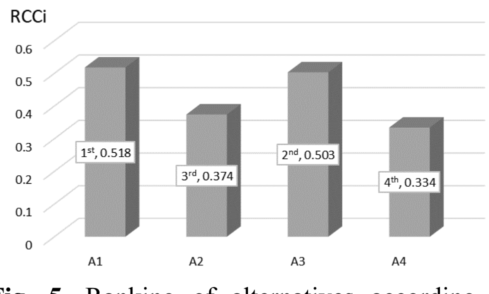

Fig. 5. Ranking of alternatives according to RCC_i values.

The result shows that the online-shopping customers are most concerned about the security of their products and least concerned about the delivery cost. This is conceivable because most online shopping comes with free delivery promotions. And it is coherent when TOPSIS ranks of the last mile deliver modes, the most preferred delivery mode is the attended home delivery. Further, the manned collection point delivery is the second one that is very close to the first preference.

8. Conclusion

The last mile delivery mode selection is a multi- criteria decision making. It concerns multi-attribute alternatives and multi-criteria decisions from the perspective of the decision-makers. This study engaged the voice of online customers who are the major stakeholders in an e-commerce business, and other businesses as well. We made use of fuzzy AHP to weigh the 8 criteria in the environment of linguistic variables. The key difference of our study is it was conducted on the large-group decision making, 1,098 decision-makers. We showed that the process of calculation was not cumbersome. All calculations could be executed on a spreadsheet package. From the weight calculation, customers were concerned much about product security and least concerned about the delivery cost.

We then made use of fuzzy TOPSIS to order four delivery modes based on the weighted criteria. The result showed that attended home delivery mode and manned collection point delivery modes are the first and the second rank in this study. It is in line with the major concerned criteria, customers care about the product security. It is worth noting that customers prefer face-to-face service and to receive the parcel by hand instead of picking it up somewhere, even at the front door of their home. Again, we showed that fuzzy TOPSIS can be conducted on the large- group decision making. The 1,098 fuzzy decision matrices could be straightforwardly calculated step- by- step on a spreadsheet package.

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