Social network multiple-criteria decision-making approach for evaluating unmanned ground delivery vehicles under the Pythagorean fuzzy environment

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Abstract: With the rapid development of instant delivery, the shrinking labor population and prevailing contact-free economy, companies have launched unmanned ground delivery vehicles (UGDVs) to replace human distribution with machines. To meet the requirements for selecting UGDVs and achieve better applications in community delivery, a multi-criteria decision-making (MCDM) framework, combining the self-confidence aggregation approach and social trust network, is proposed in this study. Based on the internal characteristics of UGDVs, a multi-criteria comprehensive evaluation system for UGDVs is constructed. Then, a trust propagation and aggregation mechanism to yield expert weights based on a social trust network is suggested. Further, a self-confidence Pythagorean fuzzy aggregation operator is proposed to enhance the credibility of the decision results and compensate for the defects of existing methods. Finally, a practical case is considered to demonstrate the complete process of the MCDM model and to conduct a comparative analysis and sensitivity analysis of the model.

Keywords: Social network; Unmanned ground delivery vehicle; Multi-criteria decision-making; Self-confidence; Pythagorean fuzzy set; Trust propagation

1. Introduction

An unmanned ground vehicle (UGV) is a type of vehicle that can accomplish autonomous perception of the surrounding environment without human intervention and can execute accurate positioning, route planning, and driving control. With the gradual development of various modern technologies, such as artificial intelligence, environmental awareness, Internet of Things, 5G, and vehicle control, UGVs have attracted wide attention and applications in many fields. In the social field, UGVs have increasingly become an important part of future intelligent transportation systems. They can replace humans to complete various tasks, such as those dealing with transportation, distribution, cleaning, patrols, and sales (Ni et al., 2020). Unmanned ground delivery vehicles (UGDVs) have shown great application potential in recent years, especially in the field of urban logistics in the last mile (Marsden et al., 2018). As an innovative solution to urban logistics, especially instant delivery, the advantages of UGDVs include (1) lowering labor cost and higher distribution efficiency compared to traditional distribution methods (e.g., couriers deliver at the distribution point and customer location using electric vehicles and automobiles), (2) realizing the delivery of goods without human contact, and (3) reducing the occurrence of distribution accidents.

Instant delivery is a highly time-sensitive delivery mode that is executed immediately after the end customer places an order online. Since 2014, instant delivery has experienced explosive growth. According to statistics, the instant delivery order volume in China in 2021 will exceed 30 billion, and the market size of instant delivery will exceed 210 billion yuan (Estar Capital, 2021). However, the external environment for instant delivery is complicated. On the one hand, the working-age population in China has been declining for seven consecutive years, resulting in a mismatch between the demand for order distribution and labor population (i.e., increasing orders and declining labor population), which has caused significant pressure on distribution and led to an increase in traffic accident rates and other social problems indirectly. On the other hand, owing to the global pandemic, community non-contact distribution services, and the rapid rise of the non-contact economy, consumer demand for home services has grown more explosively. Instant delivery products that started with takeout orders now extend to residents' daily necessities and medical products (Sumagaysay, 2020; FMI, 2020). This service also requires contactless distribution (Chen et al., 2018). In addition, there are still some problems with regard to urban logistics transportation, such as limited vehicle varieties and insufficient scenes of new energy light trucks, which directly affect environmental protection and urban logistics distribution efficiency. Thus, UGDVs have great potential for these applications.

UGDVs have become a new economic growth point in the post-pandemic era, that has also been accepted by an increasing number of people (Lemardele, et al., 2021). From the perspective of policy management, a UGDV is now considered as an efficient solution to solve the problem of instant delivery (Xinhuanet, 2020). Nuro, JingDong, Alibaba, Meituan, and other unmanned vehicle-related companies have joined the battlefield of unmanned delivery and launched their own UGDVs, which have been increasingly applied in various scenarios. At present, the White Rhino self-driving car company has taken the lead in cooperation with Yonghui Supermarket. It has invested a total of four UGDVs in the Anting Xinzhen store of Yonghui Supermarket in Shanghai, covering 5 square km (14 communities in total) and more than 6,000 households. Since October 2, 2020, all takeout orders placed by users using the Yonghui Supermarket app have been delivered through White Rhino's unmanned delivery service (Lee, 2021). Meanwhile, Meituan unmanned vehicle products have released magic bags, small bags, blessing bags, eDeliver4U, etc. The delivery services of Meituan have covered more than 20 residential areas, with a total delivery of 35,000 orders and a self-driving mileage of nearly 300,000 km. Additionally, e-commerce platforms, such as JingDong, Alibaba, and Suning have started small batch production and trial operations for UGDVs.

The requirements of the external environment and enterprise competition are constantly driving the gradual maturity of UGDV technologies. Experts have optimized the performance of unmanned vehicles from different perspectives, such as batteries and fuel cells (González et al., 2019), routing issues (Desaulnier, 2016), multi-vehicle collaborative distribution models (Boysen et al., 2018), and distribution models combined with cargo pickup stations (Ulmer & Streng, 2019). Although many researchers have proposed various methods to continuously optimize and improve the performance of UGDVs, leading to its application becoming more mature, an overall decision-making method for enterprises to choose the appropriate UGDV is still lacking. Therefore, this paper proposes a complete enterprise-oriented UGDV comprehensive MCDM system to help enterprises better choose the appropriate vehicle and achieve better application.

Currently, many theories are combined with multi-criteria decision-making (MCDM) to meet the needs of different conditions, such as fuzzy analysis (Simić, et al., 2016), soft multi-set topology (Riaz & Çagman, 2021), data envelopment analysis (Martín-Gamboa et al., 2017), and step-wise weight assessment ratio analysis (Ghenai, 2020). For UGDVs, we need to construct an effective MCDM model because a variety of factors contribute to the uncertainty in the selection and evaluation process:

(1) Due to the different factors that experts focus on, different standards are used for reaching consensus (Zhang & Hu, 2021). Taking the driving speed as an example, the speed of a mainstream UGDV on the market is controlled at 10–40 km/h, and expert judgment on the specific landing speed standard is unclear. Hence, an expert concerned with driving safety is more likely to give a higher evaluation to vehicles with a lower speed compared to other experts.

(2) Owing to different technologies, a UGDV is also affected by environmental changes. For example, lithium and lead-acid batteries are used in unmanned vehicles, but the working environment temperature of lithium batteries is stricter, and its charging temperature range is narrower (Kebede et al., 2021). Thus, variable environmental factors increase the degree of judgment inaccuracy.

(3) The description of the trust relationship among experts is inherently uncertain. Thus, an expert weight constructed by such a trust relationship is fuzzy.

Therefore, the selection of the appropriate UGDV has strong fuzziness and complexity, which is suitable for evaluation using fuzzy tools. The fuzzy set (FS)

t_p and f_p be the MD and NMD, respectively. IFS requires $t_p + f_p \in [0,1]$. However, the sum of degrees often exceeds 1 in expert opinion, such as $t_p = 0.8$ and $f_p = 0.4$, and in this case, the IFS is invalid. Therefore, Yager (2013) proposed the Pythagorean FS (PFS) and appropriately relaxed this restriction based on the IFS. Under the PFS theory, the MD and NMD satisfy the condition that the sum of squares is less than 1 as $t_p^2 + f_p^2 \in [0,1]$. Clearly, $0.8^2 + 0.4^2 < 1$ in that the PFS can be more useful in describing such an opinion. Therefore, the PFS can better describe the fuzzy information description of the MCDM than the IFS. Owing to the unique advantages of the PFS, it has been widely applied to address MCDM problems. For example, Zeng (2017) combined probabilistic information and an ordered weighted aggregation approach with the PFS. Ali et al. (2021) initiated several Einstein geometric aggregation operators by extending a novel complex interval-valued PFS for decision-making problems. Further, Çalık (2021) proposed a novel fuzzy TOPSIS and Pythagorean fuzzy AHP methodology for green supplier selection.

In summary, this paper proposes a new and complete MCDM model for a UGDV in a PFS environment. The following are the contributions of this study:

(1) Considering the unique operational processes of UGDV, this study starts with the entire operation process, disassembles the operation links in stages, forms a complete evaluation framework, and finally constructs a standard, comprehensive evaluation system for UGDVs.

(2) This study introduces a social network analysis method to determine expert

weights. Through mutual trust between experts, the influence of experts can be transformed into expert weights in the evaluation. This method of weight calculation fully considers the influence of social relations between experts on decision-making and endows the decision-making method with more objectivity and accuracy.

(3) Two new Pythagorean fuzzy self-confidence aggregation operators are proposed to compensate for the defects of existing Pythagorean fuzzy aggregation methods, which often produce unstable results when the weight difference or evaluation attitude difference is large. Thus, the presented new methods further improve the credibility of the aggregation results by integrating the expert confidence level.

The remainder of the study is organized as follows. Section 2 provides the comprehensive evaluation criteria of UGDVs and reviews relevant concepts. In Section 3, we propose the self-confidence Pythagorean weighted arithmetic and geometric aggregation operator (SC-PFWAGA), which can make up for two original operators while considering expert confidence levels. The social network analysis theory was then used for expert weight calculation. Thus, a complete social network MCDM model is presented in the PFS case. In Section 4, a specific case for the selection of the appropriate UGVD is illustrated using the proposed new MCDM approach, and a comparative analysis and parameter sensitivity test are presented. Section 5 presents policy recommendations based on research findings. Finally, Section 6 generalizes the entire paper and provides some research focus points for the future.

2. Preliminaries

2.1 Criteria for unmanned ground delivery vehicles

The criterion framework for UGDVs is constructed according to the following operation process:

(1) Pre-service stage: It refers to the preparatory work before the vehicle is put into use, mainly including the purchase of an unmanned vehicle and its supporting

equipment, as well as the early stage risk control.

(2) Use stage: It refers to the complete distribution process generated when an unmanned vehicle is put into the delivery of goods in the community. This stage can be divided into three processes and six links: (i) online operation (including collecting orders and user appraisal), (ii) loading and packing up (including loading goods and claiming goods), and (iii) "Run on the road" (including open road transport and driving into the community).

(3) Ending operation: After the vehicle completes the task, it needs to perform a series of inputs , such as charging, maintenance, and upgradation.

Based on this analysis, the three parts of the UGDV operation are divided into five second-level categories. The emphasis of each category forms the final criteria. The entire framework of the evaluation is presented in Fig. 1. The following is the detailed analysis:

(1) Purchase a vehicle with risk assessment: As the use of a UGDV is limited by budget costs and non-negligible operational risks brought by unmanned control, this part includes the initial cost (P_1), expected security risk (P_2), and safe running ability (P_3).

(2) Online operations: Online platforms generate a large amount of data. Hence, this part focuses on efficient processing of large amounts of data and ensuring information security, including platform docking efficiency (O_1), data processing efficiency (O_2), and network security (O_3).

(3) Loading and packing up: To ensure a certain amount of cargo transportation, the UGDV must provide sufficient and diversified distribution environments. Additionally, realizing efficient information interaction with people is significant. This link includes the loading capacity (L_1), quality of the distribution environment (L_2), and human-computer interaction level (L_3).

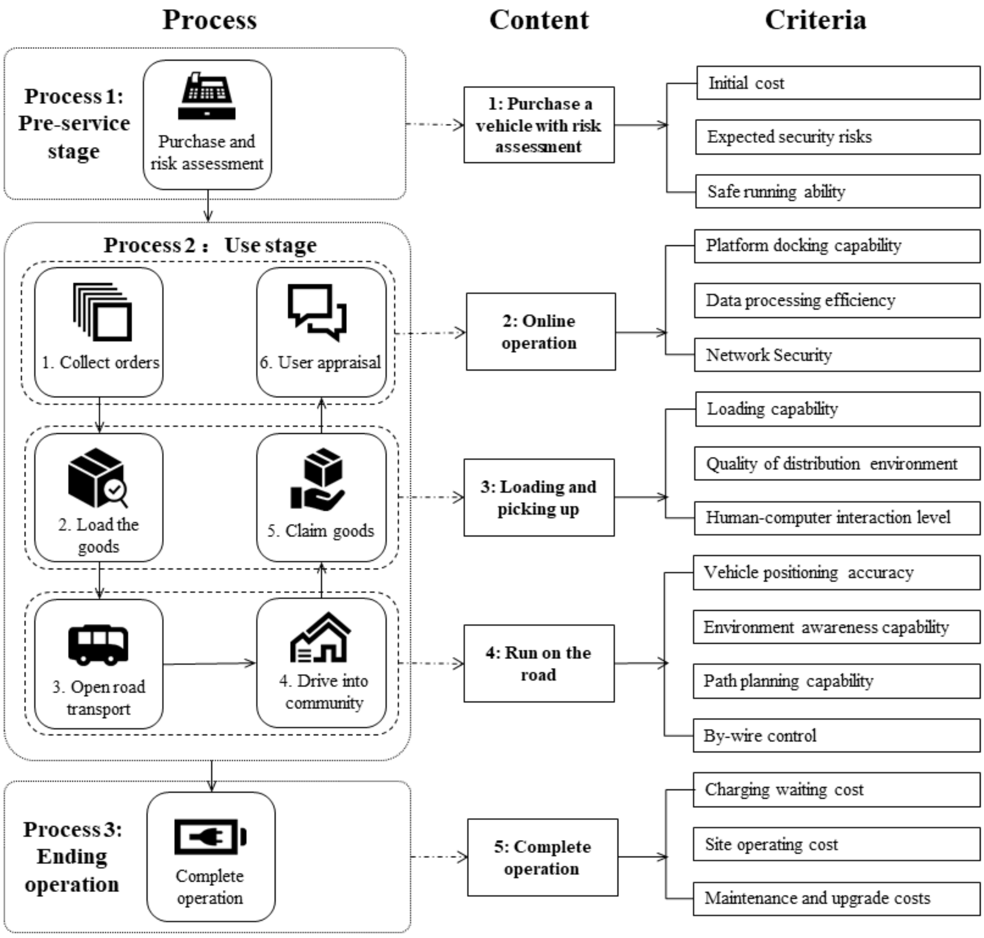


Fig. 1. Process and criteria for UGDV

(4) Run on the road: The core technology of unmanned driving is the key to the path driving ability and the basis of realizing unmanned delivery. Core technologies include vehicle positioning accuracy (R_1), environmental awareness level (R_2), path planning capability (R_3), and by-wire control ability (R_4).

(5) Complete operation: After ending an operation, a series of inputs (such as charging, maintenance, and repair) shall be made for the vehicle. At this stage, the vehicle will stop generating benefits, but incurs various costs. Therefore, this link includes the charging waiting cost (C_1), site operating cost (C_2), and maintenance and upgrade costs (C_3).

The final evaluation criteria for the UGDV and its specific explanation are presented in Table 1.

Table 1. Comprehensive evaluation criteria of the contactless distribution vehicle

Categories	Criteria	Explanation	References
Purchase a vehicle with a risk assessment	Initial cost	The total cost of purchasing unmanned delivery vehicles and related supporting equipment	Hussain and Zeadally (2019); Dylan and Miguel (2020)
	Expected security risks	The most serious damage that can occur in the event of an accident	
	Safe running ability	Machinery, sensors and computers can be driven safely without random hardware failures	
Online operation	Platform docking efficiency	The distribution system can be effectively connected with the supermarket EPR system and APP mall, etc.	Mohammed et al. (2017); Kim et al. (2021); Barry et al.(2019)
	Data processing efficiency	The distribution system is able to operate efficient path from the data	
	Network security	The security system can protect the driverless car from cyber attacks or the driving functions should be able to perform under cyber attacks	
Loading and packing up	Loading capacity	The vehicle is capable of carrying a certain amount of cargo, making efficient use of space	Sun et al. (2019); Hu et al. (2021); Guerrero-Ibáñez et al.(2015)
	Quality of distribution environment	The vehicle can customize the distribution environment for products with different characteristics, such as raw, hot, and cold	
	Human-computer interaction level	The pickers and customers can interact smoothly with delivery vehicle and delivery system	
Run on the road	Vehicle positioning accuracy	The vehicle positioning signal is stable and accurate	Bonadies and Gadsden (2018); Jong et al. (2021); Ni (2020); Demin et al. (2020)
	Environment awareness level	The vehicle is sensitive and accurate to the surrounding driving environment	
	Path planning capability	The vehicle can effectively use big data and deep learning to find the most efficient path through data	
	By-wire control	The vehicle has strong mobility and flexible driving	
Complete operation	Charging waiting cost	The potential cost of not being able to operate a vehicle while it is charging	Hannan et al. (2017); Lu (2020); Adegoke et al.
	Site operating cost	The personnel, equipment, rent and other site operation costs of the distribution	

	site	(2019);
Maintenance and upgrade costs	Cost of maintenance and upgrading of vehicle equipment and its systems	Ulmer and Streng (2019)

2.2 PFS theory

Definition 1. The Pythagorean FS (PFS) P is a mapping of a universal set X that can be expressed in the following form:

$$P=\left\{x,t_P(x),f_P(x)\middle|x\in X\right\}, \quad (1)$$

where $0\le t_P(x)\le 1$, $0\le f_P(x)\le 1$, and $0\le t_A^2(x)+f_A^2(x)\le 1$. Further, $t_P(x)$ and $f_P(x)$ represent the MD and NMD of the element $x\in X$ in P, respectively. The hesitation degree is given as $\pi_P(x)=\sqrt{1-t_P^2(x)-f_P^2(x)}$. For simplicity, $\alpha=\langle t_P,f_P\rangle$ is the Pythagorean fuzzy number (PFN). The score function is denoted by sc, and the accuracy function is represented by ac.

$$sc(\alpha)=t_p^2-f_p^2, \quad (2)$$

$$ac(\alpha)=t_p^2+f_p^2, \quad (3)$$

where $sc(\alpha)\in[-1,1]$ and $ac(\alpha)\in[0,1]$. If $sc(\alpha_1)<sc(\alpha_2)$, then $\alpha_1\prec\alpha_2$; if $sc(\alpha_1)>sc(\alpha_2)$, then $\alpha_1\succ\alpha_2$; and if $sc(\alpha_1)=sc(\alpha_2)$, then three cases according to the accuracy function shall be considered: (1) if $ac(\alpha_1)<ac(\alpha_2)$, then $\alpha_1\prec\alpha_2$; (2) if $ac(\alpha_1)>ac(\alpha_2)$, then $\alpha_1\succ\alpha_2$; and (3) if $ac(\alpha_1)=ac(\alpha_2)$, then $\alpha_1=\alpha_2$.

Definition 2. Basic operation rules: Let λ be a real number and $\lambda>0$, $\alpha=\langle t,f\rangle$, $\alpha_1=\langle t_1,f_1\rangle,\alpha_2=\langle t_2,f_2\rangle$ and be three PFNs.

(1) $\alpha_1\oplus\alpha_2=\left\langle\sqrt{(t_1)^2+(t_2)^2-(f_1)^2(f_2)^2},f_1f_2\right\rangle$;

(2) $\alpha_1\otimes\alpha_2=\left\langle t_1t_2,\sqrt{(t_1)^2+(t_2)^2-(f_1)^2(f_2)^2}\right\rangle$;

(3) $\lambda\alpha=\left\langle\sqrt{1-(1-t^2)^\lambda},f^\lambda\right\rangle$;

(4) $\alpha^\lambda=\left\langle t^\lambda,\sqrt{1-(1-f^2)^\lambda}\right\rangle$.

To infuse Pythagorean fuzzy information, Yager (2014) proposed the Pythagorean fuzzy weighted arithmetic average (PFWA) and Pythagorean fuzzy weighted geometric average (PFGA) operators.

Definition 3. Let $A = \{\alpha_1, \alpha_2, \cdots, \alpha_n\}$ be a set of PFNs, where $\alpha_i = \langle t_i, f_i \rangle$. A PFWA and PFGA operator of dimension *n*, which have a relative weighting vector $W = \{w_1, w_2, \cdots, w_n\}$ with $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j = 1$, are defined in the following form:

$$H_{PFWA(<t_1,f_1>,\ldots,<t_n,f_n>)} = \sum_{j=1}^{n} w_j \alpha_j = \left\langle \sqrt{1 - \prod_{j=1}^{n} (1 - (t_j)^2)^{w_j}}, \prod_{j=1}^{n} (f_j)^{w_j} \right\rangle, \qquad (4)$$

and

$$H_{PFGA(<t_1,f_1>,\ldots,<t_n,f_n>)} = \prod_{j=1}^{n} \alpha_j^{w_j} = \left\langle \prod_{j=1}^{n} t_j^{w_j}, \sqrt{1 - \prod_{j=1}^{n} (1 - f_j^2)^{w_j}} \right\rangle. \qquad (5)$$

2.3 Consensus measure

Definition 4. Let k experts form a decision group $E = \{e_1, e_2, \ldots, e_k\}$ based on weight $\omega = \{\omega_1, \omega_2 \ldots \omega_k\}^T$. The expert decision matrix on a finite set of alternatives $X = \{x_1, x_2 \ldots\ldots, x_n\}$ and a set of criteria $C = \{c_1, c_1 \ldots c_m\}$ are denoted by $R^h = (R_{ij}^h)_{n \times m}$, where $R_{ij}^h = (\alpha_{ij}^h, \mu_{ij}^h)$ represents the evaluation of expert e_h on alternative x_i with criteria c_j. Additionally, α_{ij}^h is a set of PFNs about expert evaluation value, and μ_{ij}^h is the expert confidence level.

$$R^h = \left[R_{ij}^h \right] = \begin{bmatrix} R_{11}^h & R_{12}^h & \cdots & R_{1m}^h \\ R_{21}^h & R_{22}^h & \cdots & R_{2m}^h \\ \vdots & \vdots & \vdots & \vdots \\ R_{n1}^h & R_{n2}^h & \cdots & R_{nm}^h \end{bmatrix}$$

The group decision matrix is defined as $\overline{R} = \left[\overline{R_{ij}} = (\overline{\alpha_{ij}}, \overline{\mu_{ij}}) \right]$

$\overline{\alpha_{ij}}$ is the collective evaluation value, and $\overline{\mu_{ij}}$ represents the collective confidence level of the expert group.

After obtaining the evaluation value of each expert and group decision matrix, the consensus level among experts should be measured. To obtain the consensus degree of the expert, consensus measurement can be computed at three levels for each expert: (1) element level, (2) alternative level, and (3) judgment level (Wu et al., 2017).

Level 1: At the element level. The consensus degree of e_h on alternatives x_i with criteria c_j is defined as follows:

$$\mathrm{CE}_{ij}^{h} = 1 - \sqrt{\frac{(\overline{t_{ij}} - t_{ij}^{h})^2 + (\overline{f_{ij}} - f_{ij}^{h})^2}{2}}. \tag{6}$$

Level 2: At the alternative level. The consensus degree of e_h on the alternative x_i is defined as follows:

$$\mathrm{ACE}_{i}^{h} = \frac{1}{m}\sum_{j}^{m}\mathrm{CE}_{ij}^{h}. \tag{7}$$

Level 3: At the expert level. The consensus degree of e_h is defined as follows:

$$\mathrm{AUE}^{h} = \frac{1}{n}\sum_{i}^{n}\mathrm{ACE}_{i}^{h}. \tag{8}$$

The greater the value of AUE^h, the greater the degree of consensus between the individual expert and the group. In addition to measuring the consensus level, the three-level consensus degree can help identify evaluations that fall short of the consensus level efficiently. The consensus threshold is set to γ. Once the AUE^h threshold is less than the predefined threshold γ, there is some evaluation that does e_h not reach a consensus with the decision group. The specific steps were analyzed as follows:

Step 1. Experts with a consensus degree at an expert level lower than the threshold value γ were determined:

$$EXPCH = \{h \mid AUE^h < \gamma\}.$$

Step 2. For the identified experts in Step 1, their consensus degrees at alternative levels lower than the threshold value γ are clarified:

$$ALT = \{(h,i) \mid h \in EXPCH \wedge \mathrm{ACE}_i^h < \gamma\}.$$

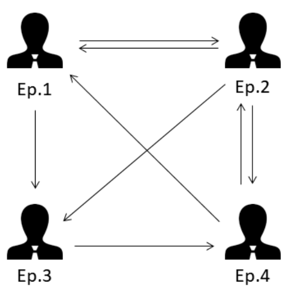
Step 3. Finally, the evaluation values to be changed are those with the following consensus criteria:

$$APS = \{(h,i,j) \mid (h,i) \in ALT \wedge \mathrm{CE}_{ij}^h < \gamma\}.$$

2.4 Social network and trust score

A social network (Wu et al., 2017) can be regarded as a collection comprising multiple individuals, through which they communicate and transmit information and carry out corresponding social activities. The social network consists of individuals, social relations, and individual weights, and the trust relationship between these individuals is generated and transmitted, along with the trust between people.

Table 2. Several forms of the social network

Graph	Algebraic	Adjacency Matrix	Accessibility Matrix
	e_1te_2 e_1te_3 e_2te_1 e_2te_3 e_2te_4 e_3te_4 e_4te_1 e_4te_2	$\mathrm{A} = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 \end{pmatrix}$	$\mathrm{B} = \begin{pmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}$

Trust relationships between experts can be expressed in various ways. A panel of four experts is shown in Table 2, where the arrows indicate the trust relationships among them. Algebra is also a good technique to assess trust, as e_1 e_2

e_1te_2

e_1 trusts e_2 and e_2 trusts e_4, it sets $A[1,2]=1$ and $A[2,4]=1$ separately. No direct trust exists from expert e_1 to e_4 shown in the graph of Table 2, which appears as $A[1,4]=0$. However, an indirect trust relationship can be generated between e_1 and e_4 by propagating through e_2, which is represented in the accessible matrix as $B[1,4]=1$.

However, defects in the trust expression methods of 0 and 1 are evident. In a real society, a relationship wherein a person is either completely trusting or completely distrusting is difficult to exist. The degree of trust can be different and uncertain. Therefore, in this study, the PFN is used to express the trust relationship among experts, and the concepts of trust relationship and trust score (TS) are defined on this basis.

Definition 5. Trust Relationship: Let $\sigma_{ij}=\langle t_{ij}, f_{ij}\rangle$ be a set of PFNs, where $0 \le t_{ij} \le 1, 0 \le f_{ij} \le 1$, and $t_{ij}^2 + f_{ij}^2 \le 1$. Further, σ_{ij} represents the trust relationship from e_i to e_j, where t_{ij} represents how much e_i trust e_j and f_{ij} represents how much e_i distrust e_j.

Moreover, a TS can be defined as

$$\mathrm{TS}\left(\sigma_{ij}\right)=t_{ij}^2 - f_{ij}^2, \tag{9}$$

where $-1<\mathrm{TS}<1$. A TS positive value indicates trust. The closer the TS value to 1, the stronger the trust relationship. When the TS value is negative, it indicates distrust, and the closer the TS value to -1, the greater the degree of distrust. For example, $\sigma_{12}=\langle 0.7, 0.3\rangle$ implies the existence of a trust relationship from e_1 to e_2 and the TS of 0.4.

3. MCDM model based on the SC-PFWAGA operator and social network

3.1 PFWAGA operator

In existing PFWA and PFGA operators, when some values tend to be the maximum independent variable and the maximum weight, their aggregation results may produce some unreasonable results (Ye, 2017). The following example illustrates this issue:

Example 1. Two PFNs, $\alpha_1 = \langle 0.1, 0 \rangle$ and $\alpha_2 = \langle 1, 0 \rangle$, with their weights $w_1 = 0.5$ and $w_2 = 0.5$. By using Eqs. (8) and (9), we obtain

$$H_{PFWA(\alpha_1,\alpha_2)} = \left\langle \sqrt{1-(1-0.1^2)^{0.5} \times (1-1^2)^{0.5}}, 0 \right\rangle = \langle 1, 0 \rangle,$$

$$H_{\mathrm{PFGA}(\alpha_1,\alpha_2)} = \left\langle 0.1^{0.5} \times 1^{0.5}, 0 \right\rangle = \langle 0.316, 0 \rangle.$$

If the weights are changed to $w_1 = 0.1$ and $w_2 = 0.9$, then

$$H_{PFWA(\alpha_1,\alpha_2)} = \left\langle \sqrt{1-(1-0.1^2)^{0.1} \times (1-1^2)^{0.9}}, 0 \right\rangle = \langle 1, 0 \rangle,$$

$$H_{PFGA(\alpha_1,\alpha_2)} = \left\langle 0.1^{0.1} \times 1^{0.9}, 0 \right\rangle = \langle 0.722, 0 \rangle.$$

It can be observed that the calculation results of the PFWA and PFGA operators may differ greatly when the weights are fixed and the input PFNs are clearly different. Additionally, if the weight difference is evident, the aggregation result of the two operators remains unstable.

Therefore, a new Pythagorean fuzzy weighted arithmetic and geometric aggregation operator (PFWAGA) is proposed to compensate for the unstable aggregation effect of existing PFWA and PFGA operators. It can be represented in two ways (i.e., PFWAGA1 and PFWAGA2) depending on the aggregation method.

Definition 6. Let $A = \{\alpha_1, \alpha_2, \cdots, \alpha_n\}$ be a set of PFNs, where $\alpha_i = \langle t_i, f_i \rangle$. Let the weighting vector be $W = \{w_1, w_2, \cdots, w_n\}$ with $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j = 1$, λ and be the adjustment coefficient. The PFWAGA1 and PFWAGA2 operators are defined as follows:

$$H_{PFWAGA1(<t_1,f_1>,\ldots,<t_n,f_n>)} = (\sum_{j=1}^{n} w_j \alpha_j)^{\lambda} \otimes (\prod_{j=1}^{n} \alpha_j^{\,w_j})^{1-\lambda}$$

$$= \left\langle \left[1-\prod_{j=1}^{n}\left(1-t_j^{\,2}\right)^{w_j}\right]^{\frac{\lambda}{2}} \prod_{j=1}^{n} t_j^{\,w_j(1-\lambda)}, \sqrt{1-(1-\prod_{j=1}^{n} f_j^{\,2w_j})^{\lambda} \prod_{j=1}^{n}(1-f_j^{\,2})^{w_j(1-\lambda)}} \right\rangle, \quad (10)$$

$$H_{PFWAGA2(<t_1,f_1>,\ldots,<t_n,f_n>)} = \lambda \sum_{j=1}^{n} w_j \alpha_j \oplus (1-\lambda) \prod_{j=1}^{n} \alpha_j^{\,w_j}$$

$$= \left\langle \sqrt{1-\left(1-\prod_{j=1}^{n} t_j^{\,2w_j}\right)^{1-\lambda} \prod_{j=1}^{n}\left(1-t_j^{\,2}\right)^{w_j\lambda}}, \left[1-\prod_{j=1}^{n}\left(1-f_j^{\,2}\right)^{w_j}\right]^{\frac{1-\lambda}{2}} \prod_{j=1}^{n} f_j^{\,w_j\lambda} \right\rangle. \quad (11)$$

The complete proof of Eqs. (10) and (11) are as follows:

$$H_{PFWAGA1(<t_1,f_1>,\ldots,<t_n,f_n>)} = (\sum_{j=1}^{n} w_j \alpha_j)^{\lambda} \otimes (\prod_{j=1}^{n} \alpha_j^{\,w_j})^{1-\lambda}$$

$$= \left\langle \sqrt{1-\prod_{j}^{n}(1-t_j^2)^{w_j}}, \prod_{j}^{n}(f_j)^{w_j} \right\rangle^{\lambda} \otimes \left\langle \prod_{j}^{n}(t_j)^{w_j}, \sqrt{1-\prod_{j}^{n}(1-f_j^2)^{w_j}} \right\rangle^{1-\lambda}$$

$$= \left\langle \left[\sqrt{1-\prod_{j}^{n}(1-t_j^2)^{w_j}}\right]^{\lambda}, \sqrt{1-\left[1-\prod_{j}^{n}(f_j)^{w_j}\right]^{\lambda}} \right\rangle \otimes \left\langle \prod_{j}^{n}(t_j)^{w_j(1-\lambda)}, \sqrt{1-\prod_{j}^{n}(1-f_j^2)^{w_j(1-\lambda)}} \right\rangle$$

$$= \left\langle \left[1-\prod_{j=1}^{n}\left(1-t_j^{\,2}\right)^{w_j}\right]^{\frac{\lambda}{2}} \prod_{j=1}^{n} t_j^{\,w_j(1-\lambda)}, \sqrt{1-(1-\prod_{j=1}^{n} f_j^{\,2w_j})^{\lambda} \prod_{j=1}^{n}(1-f_j^{\,2})^{w_j(1-\lambda)}} \right\rangle,$$

$$H_{PFWAGA2(<t_1,f_1>,\ldots,<t_n,f_n>)} = \lambda \sum_{j=1}^{n} w_j \alpha_j \oplus (1-\lambda) \prod_{j=1}^{n} \alpha_j^{\,w_j}$$

$$= \lambda \left\langle \sqrt{1-\prod_{j}^{n}(1-t_j^2)^{w_j}}, \prod_{j}^{n}\left(f_j\right)^{w_j} \right\rangle \oplus (1-\lambda) \left\langle \prod_{j}^{n}\left(t_j\right)^{w_j}, \sqrt{1-\prod_{j}^{n}\left(1-f_j^2\right)^{w_j}} \right\rangle$$

$$= \left\langle \sqrt{1-\prod_{j}^{n}(1-t_j^2)^{w_j\lambda}}, \prod_{j}^{n}\left(f_j\right)^{w_j\lambda} \right\rangle \oplus \left\langle \sqrt{1-\left(1-\prod_{j}^{n}\left(t_j\right)^{w_j}\right)^{1-\lambda}}, \left[1-\prod_{j}^{n}\left(1-f_j^2\right)^{w_j}\right]^{\frac{1-\lambda}{2}} \right\rangle.$$

$$= \left\langle \sqrt{1-\left(1-\prod_{j=1}^{n} t_j^{\,2w_j}\right)^{1-\lambda} \prod_{j=1}^{n}\left(1-t_j^{\,2}\right)^{w_j\lambda}}, \left[1-\prod_{j=1}^{n}\left(1-f_j^{\,2}\right)^{w_j}\right]^{\frac{1-\lambda}{2}} \prod_{j=1}^{n} f_j^{\,w_j\lambda} \right\rangle.$$

Example 2. Take two PFNs, $\alpha_1 = \langle 0.1, 0 \rangle$ and $\alpha_2 = \langle 0.9, 0 \rangle$, with their weights $w_1 = 0.5$ and $w_2 = 0.5$. Let $\lambda = 0.5$, and using Eqs. (10) and (11), we obtain

$$H_{PFWAGA1(\alpha_1,\alpha_2)} = \left\langle \left[1-\left(1-0.1^2\right)^{0.5}\times\left(1-0.9^2\right)^{0.5}\right]^{0.25}\times 0.1^{0.25}\times 0.9^{0.25}, \sqrt{1-(1-0^1\times 0^1)^{0.5}} \right\rangle$$
$$= \langle 0.475, 0 \rangle,$$

$$H_{PFWAGA2(\alpha_1,\alpha_2)} = \left\langle \sqrt{1-\left(1-0.1\times 0.9\right)^{0.5}\times\left(1-0.1^2\right)^{0.25}\times\left(1-0.9^2\right)^{0.25}}, [1-1]^{0.25}\times 0 \right\rangle$$
$$= \langle 0.609, 0 \rangle.$$

Specifically, if weights are changed to $w_1 = 0.1$ and $w_2 = 0.9$, then

$$H_{PFWAGA1(\alpha_1,\alpha_2)} = \left\langle \left[1-\left(1-0.1^2\right)^{0.1}\times\left(1-0.9^2\right)^{0.9}\right]^{0.25}\times 0.1^{0.05}\times 0.9^{0.45}, \sqrt{1-(1-0^{0.1}\times 0^{1.8})^{0.5}} \right\rangle$$
$$= \langle 0.797, 0 \rangle,$$

$$H_{PFWAGA2(\alpha_1,\alpha_2)} = \left\langle \sqrt{1-\left(1-0.1^{0.1}\times 0.9^{1.8}\right)^{0.5}\times\left(1-0.1^2\right)^{0.05}\times\left(1-0.9^2\right)^{0.45}}, [1-1]^{0.25}\times 0 \right\rangle$$
$$= \langle 0.82, 0 \rangle.$$

Compared with the results of Example 1, the variation range of the aggregation results of PFWAGA1 and PFWAGA2 operators is clearly more controllable, regardless of how much the weights are changed. This indicates that the improved method can compensate for the instability of the aggregation results of existing operators.

3.2 SC-PFWAGA operator

Existing operators assume that experts are fully familiar with the evaluation criteria of each product and have full confidence in making judgments, ignoring the impact of the expert confidence level. That is, if the experts do not have full confidence during decision-making, then the corresponding weights need to be discounted (Ji et al., 2020; Garg, 2017). Therefore, based on PFWAGA1 and PFWAGA2 operators defined in Subsection 3.1, we propose SC-PFWAGA1 and SC-PFWAGA2 operators, incorporating the confidence level.

Definition 7. Let $A = \{\alpha_1, \alpha_2, \cdots, \alpha_n\}$ $\alpha_i = \langle t_i, f_i \rangle$. Let the

$W=\{w_1,w_2,\cdots,w_n\}$ with $0\le w_j\le 1$, $\sum_{j=1}^{n} w_j=1$, and the confidence level vector $U=\{\mu_1,\mu_2,...,\mu_n\}$ with $0\le\mu_j\le 1$, where λ is the adjustment coefficient. Specifically, SC-PFWAGA1 and SC-PFWAGA2 operators are defined as follows:

$$H_{SC-PFWAGA1((\alpha_1,\mu_1),...,(\alpha_n,\mu_n))}=\left(\sum_{j=1}^{n} w_j\left(\mu_j\alpha_j\right)\right)^{\lambda}\otimes\left(\prod_{j=1}^{n}\alpha_j^{\mu_j w_j}\right)^{1-\lambda}$$
$$=\left\langle\left[1-\prod_{j=1}^{n}\left(1-t_j^{\,2}\right)^{\mu_j w_j}\right]^{\frac{\lambda}{2}}\prod_{j=1}^{n}t_j^{\,\mu_j w_j(1-\lambda)},\sqrt{1-(1-\prod_{j=1}^{n}f_j^{\,2\mu_j w_j})^{\lambda}\prod_{j=1}^{n}(1-f_j^{\,2})^{\mu_j w_j(1-\lambda)}}\right\rangle, \quad (12)$$

$$H_{SC-PFWAGA2((\alpha_1,\mu_1),...,(\alpha_n,\mu_n))}=\lambda\sum_{j=1}^{n} w_j\left(\mu_j\alpha_j\right)\oplus(1-\lambda)\prod_{j=1}^{n}\alpha_j^{\mu_j w_j}$$
$$=\left\langle\sqrt{1-\left(1-\prod_{j=1}^{n}t_j^{\,2\mu_j w_j}\right)^{1-\lambda}\prod_{j=1}^{n}\left(1-t_j^{\,2}\right)^{\mu_j w_j\lambda}},\left[1-\prod_{j=1}^{n}\left(1-f_j^{\,2}\right)^{\mu_j w_j}\right]^{\frac{1-\lambda}{2}}\prod_{j=1}^{n}f_j^{\,\mu_j w_j\lambda}\right\rangle. \quad (13)$$

The complete proof of Eqs. (12) and (13) are as follows:

$$H_{SC-PFWAGA1((\alpha_1,\mu_1),...,(\alpha_n,\mu_n))}=\left(\sum_{j=1}^{n} w_j\left(\mu_j\alpha_j\right)\right)^{\lambda}\otimes\left(\prod_{j=1}^{n}\alpha_j^{\mu_j w_j}\right)^{1-\lambda}$$
$$=\left\langle\sqrt{1-\prod_{j}^{n}\left(1-t_j^2\right)^{\mu_j w_j}},\prod_{j}^{n}\left(f_j\right)^{\mu_j w_j}\right\rangle^{\lambda}\otimes\left\langle\prod_{j}^{n}\left(t_j\right)^{\mu_j w_j},\sqrt{1-\prod_{j}^{n}\left(1-f_j^2\right)^{\mu_j w_j}}\right\rangle^{1-\lambda}$$
$$=\left\langle\left[\sqrt{1-\prod_{j}^{n}\left(1-t_j^2\right)^{\mu_j w_j}}\right]^{\lambda},\sqrt{1-\left[1-\prod_{j}^{n}\left(f_j\right)^{\mu_j w_j}\right]^{\lambda}}\right\rangle\otimes\left\langle\prod_{j}^{n}\left(t_j\right)^{\mu_j w_j(1-\lambda)},\sqrt{1-\prod_{j}^{n}\left(1-f_j^2\right)^{\mu_j w_j(1-\lambda)}}\right\rangle$$
$$=\left\langle\left[1-\prod_{j=1}^{n}\left(1-t_j^{\,2}\right)^{\mu_j w_j}\right]^{\frac{\lambda}{2}}\prod_{j=1}^{n}t_j^{\,\mu_j w_j(1-\lambda)},\sqrt{1-\left(1-\prod_{j=1}^{n}f_j^{\,2\mu_j w_j}\right)^{\lambda}\prod_{j=1}^{n}\left(1-f_j^{\,2}\right)^{\mu_j w_j(1-\lambda)}}\right\rangle,$$

$$H_{SC-PFWAGA2((\alpha_1,\mu_1),\ldots,(\alpha_n,\mu_n))} = \lambda\sum_{j=1}^{n} w_j(\mu_j\alpha_j) \oplus (1-\lambda)\prod_{j=1}^{n}\alpha_j^{\mu_j w_j}$$

$$= \lambda\left\langle \sqrt{1-\prod_{j}^{n}\left(1-t_j^2\right)^{\mu_j w_j}}, \prod_{j}^{n}\left(f_j\right)^{\mu_j w_j} \right\rangle \oplus (1-\lambda)\left\langle \prod_{j}^{n}\left(t_j\right)^{\mu_j w_j}, \sqrt{1-\prod_{j}^{n}\left(1-f_j^2\right)^{\mu_j w_j}} \right\rangle$$

$$= \left\langle \sqrt{1-\prod_{j}^{n}\left(1-t_j^2\right)^{\mu_j w_j \lambda}}, \prod_{j}^{n}\left(f_j\right)^{\mu_j w_j \lambda} \right\rangle \oplus \left\langle \sqrt{1-\left(1-\prod_{j}^{n}\left(t_j\right)^{\mu_j w_j}\right)^{1-\lambda}}, \left[1-\prod_{j}^{n}\left(1-f_j^2\right)^{\mu_j w_j}\right]^{\frac{1-\lambda}{2}} \right\rangle$$

$$= \left\langle \sqrt{1-\left(1-\prod_{j=1}^{n} t_j^{2\mu_j w_j}\right)^{1-\lambda} \prod_{j=1}^{n}\left(1-t_j^2\right)^{\mu_j w_j \lambda}}, \left[1-\prod_{j=1}^{n}\left(1-f_j^2\right)^{\mu_j w_j}\right]^{\frac{1-\lambda}{2}} \prod_{j=1}^{n} f_j^{\mu_j w_j \lambda} \right\rangle.$$

Example 3. Take two PFNs $\alpha_1 = \langle 0.1, 0\rangle$ $\alpha_2 = \langle 0.9, 0\rangle$ with their weights $w_1 = 0.5$ and $w_2 = 0.5$. The confidence levels are assumed to be $\mu_1 = 0.6$ and $\mu_2 = 0.9$. Let $\lambda = 0.5$. Using Eqs. (12) and (13), we obtain

$$H_{SC-PFWAGA1(\alpha_1,\alpha_2)}$$

$$= \left\langle \left[1-\left(1-0.1^2\right)^{0.1\times0.6} \times \left(1-0.9^2\right)^{0.9\times0.9}\right]^{0.25} \times 0.1^{0.25\times0.6} \times 0.9^{0.25\times0.9}, \sqrt{1-(1-0^{0.6}\times 0^{0.9})^{0.5}} \right\rangle$$

$$= \langle 0.5892, 0\rangle,$$

$$H_{SC-PFWAGA1(\alpha_1,\alpha_2)}$$

$$= \left\langle \sqrt{1-\left(1-0.1^{0.2\times0.6}\times 0.9^{1.8\times0.9}\right)^{0.5} \times \left(1-0.1^2\right)^{0.05\times0.9} \times \left(1-0.9^2\right)^{0.45\times0.9}}, [1-1]^{0.06}\times 0 \right\rangle$$

$$= \langle 0.6296, 0\rangle.$$

If the weights change to $w_1 = 0.1$ and $w_2 = 0.9$, then

$$H_{SC-PFWAGA1(\alpha_1,\alpha_2)}$$

$$= \left\langle \left[1-\left(1-0.1^2\right)^{0.1\times0.6} \times \left(1-0.9^2\right)^{0.9\times0.9}\right]^{0.25} \times 0.1^{0.05\times0.6} \times 0.9^{0.45\times0.9}, \sqrt{1-(1-0^{0.1\times0.6}\times 0^{1.8\times0.9})^{0.5}} \right\rangle$$

$$= \langle 0.8293, 0\rangle,$$

$H_{SC-PFWAGA2(\alpha_1,\alpha_2)}$

$$=\left\langle \sqrt{1-\left(1-0.1^{0.1\times0.6}\times0.9^{1.8\times0.9}\right)^{0.5}\times\left(1-0.1^2\right)^{0.05\times0.9}\times\left(1-0.9^2\right)^{0.45\times0.9}},[1-1]^{0.25}\times0\right\rangle$$

$$=\langle 0.8329,0\rangle.$$

Compared with the PFWAGA operator, the SC-PFWAGA operator can infuse expert confidence in the aggregation result, and the expert confidence level further affects the final aggregation result through weight adjustment. Because of the introduction of the confidence level, the influence of the experts' psychological behavior on the results was understood, and the stability of the results was maintained. Moreover, SC-PFWAGA is reduced to the PFWAGA operator if $\mu_i=1$.

3.3 Expert weights based on trust networks

An important step in solving the MCDM problem in a Pythagorean fuzzy environment is to calculate the weights of experts. In most existing studies, researchers often determine the weight of experts according to their experience, knowledge, education, and other factors. However, this method is subjective and unreliable. Because interpersonal relationships can be clearly and effectively expressed in social networks, various approaches for calculating expert weights using social networks are developing rapidly. In this subsection, we propose a calculation method for expert weight using social network analysis under a Pythagorean fuzzy environment.

Generally, the trust information between experts in a social network is incomplete, and hence there will be a lack of trust relationships between experts. Therefore, these true trust relationships should be completed (Wu, 2017). Subsequently, we develop the trust propagation equation and final trust relationship.

Definition 8. Trust propagation: There are two trust values, namely, $\sigma_{12}=\langle t_{12},f_{12}\rangle$

$\sigma_{23}=\langle t_{23},f_{23}\rangle$ e_1 to e_2 and e_2 to e_3, where $t_{12}, f_{12}, t_{23}, f_{23} \in (0,1)$, ${t_{12}}^2 + {f_{12}}^2 \le 1$, and ${t_{23}}^2 + {f_{23}}^2 \le 1$. The trust propagation formula between them is as follows:

$$TP(\sigma_{12}, \sigma_{23}) = \left\langle \frac{t_{12} \times t_{23}}{1 + (1 - t_{12})(1 - t_{23})}, \frac{f_{12} + f_{23}}{1 + f_{12} \times f_{23}} \right\rangle. \tag{14}$$

Definition 9. If no direct trust relationship exists from e_i to e_j, then there are N paths for trust propagation, $L = \{l_1, l_2, \ldots, l_N\}$. Let $\sigma_{ij}^{l_t}$ represent the trust relationship from e_i to e_j be implemented through path l_t. Then, the final trust relationship from e_i to e_j can be expressed as

$$\sigma_{ij} = H_{PFWAGA1(\sigma_{ij}^{l_1}, \sigma_{ij}^{l_1}, \ldots, \sigma_{ij}^{l_N})}, \tag{15}$$

or

$$\sigma_{ij} = H_{PFWAGA2(\sigma_{ij}^{l_1}, \sigma_{ij}^{l_1}, \ldots, \sigma_{ij}^{l_N})},$$

where the weight can be set as $\frac{n_i}{\sum_i n_i}$ and n_i represents the number of trust passes required in path l_i.

According to the trust relationship among experts, experts with higher TSs have higher discourse power and should be given more weight. Subsequently, based on the TS determined by Eq.(9), the degree to which the experts are trusted is obtained as

$$OT_h = \frac{1}{k} \sum_{i=1}^{k} TS(\sigma_{ih}). \tag{16}$$

A higher OT_h represents that expert e_h gains more trust from others. Finally, the expert weight ω_h can be obtained by normalization OT_h.

3.4 Weights of criteria

Criteria weight plays a vital role in the MCDM problem and has a significant influence on the final decision result. The current methods of the MCDM mainly include analytic hierarchy process (AHP; Saaty, 1987), best worst method (BWM; Rezaei, 2015), level-based weight assessment (LBWA; Žižović & Pamucar, 2019), and complete consistency method (FUCOM; Pamučar et al., 2018). Although the BWM is superior to AHP in terms of minimum violation, total deviation, and conformity, the comparison between the criteria also imposes clear limitations on nonlinear model solving, which also leads to many complexities in its application (Žižović & Pamucar, 2019). Both FUCOM and LBWA methods require only n-1 criteria in pairwise comparison, which is the minimum comparison quantity, but further calculation of FUCOM is complicated. The complexity of LBWA can be controlled in the case of increasing criteria. Hence, it is more suitable in the case of multi-criteria comparison.

AHP is one of the most commonly used tools in MCDM problems (D'Adamo et al., 2020; Zyoud & Fuchs-Hanusch, 2017), information and communication technology (Oztaysi, 2014), unmanned equipment selection (Hamurcu & Eren, 2020), and safe transportation (Gumus, 2008), among others. It also has many advantages, such as simplicity, ease of application, flexibility, integration with various methods, and tolerant rapid re-planning, which helps in obtaining accurate decision estimation from the judgment of various experts. The degree of consistency of pairwise comparisons can also be determined.

Consequently, a MCDM methodology integrated with AHP is suitable for assessing the UGDV. Initially, based on the process and criteria for UGDVs, this study defines two limited weight levels to calculate the weight of indicators hierarchically. These levels are (1) local priority weight of criteria and (2) group priority weight of category. Each expert provides six comparison matrices (five for local priority weight and one for group priority weight) according to the nine-point method $A^h = (a_{ij}^h)_{n\times n}$ a_{ij}^h represents the importance of criterion i to j in expert e_h. The coincidence indicator C_I and random consistency index C_R were calculated. When $C_R < 0.1$, it passes the consistency test; otherwise, it needs to be adjusted by the experts. Then, we calculate the average geometric results from the row, normalize them, and obtain w_i. Thus, the final weight of each criterion obtained by expert e_h is

$$w^{global,h} = w^{group,h} \times w^{local,h}, \quad (17)$$

where $w^{global,h}$ represents the final weight of the given criteria by expert e_h. Then, the final criteria weight is yielded as

$$w^{global} = \frac{1}{k}\sum_{h=1}^{k} w^{global,h} \times \omega_h \quad . \quad (18)$$

3.5 Steps and flow of the MCDM model

Before the evaluation of unmanned delivery vehicles, a group of experts $E = \{e_1, e_2, ..., e_k\}$ from various industries should be established. The weights of the experts were denoted by $\omega = \{\omega_1, \omega_2 \ldots \omega_k\}$. The expert group conducted a comprehensive evaluation of n the alternative brands of UGDVs $A = \{A_1, A_2 \ldots A_n\}$. The evaluation criteria are denoted by $\mathrm{C} = \{C_1, C_2 \ldots C_m\}$ weight $w = \{w_1, w_2 \ldots w_m\}$. To express expert judgment accurately, PFNs are used to convey the relationship between expert judgment and expert trust. The specific decision-making process is shown in Fig. 2. The detailed steps are described as follows:

Step 1. Use PFNs to express trust in relationships with others. A trust network matrix is established. Trust propagation was carried out using Eqs. (14)–(15), and the adjacency matrix changes into the accessibility matrix. Finally, the weights of the experts ω_h can be calculated according to Eq. (16).

Step 2. Calculate the criteria weight using the AHP method. Experts make comparison matrices in two limited weight levels, the local priority weight of criteria, and group priority of category. Then, the final criteria weight is calculated using Eqs. (17) and (18), respectively.

Step 3. Experts provide the decision matrix $R^h = (R^h_{ij})_{n\times m}\left(h = 1, 2, ..., k\right)$

$R^h_{ij} = \left(\alpha^h_{ij}, \mu^h_{ij}\right)$ e_h on criteria C_j of alternative A_i, α_{ij}^h is a set of PFNs of the evaluation value, and μ_{ij}^h is the confidence level.

Step 4. Compute the group decision matrix, $\overline{R} = \left[\overline{R_{ij}} = (\overline{\alpha_{ij}}, \overline{\mu_{ij}})\right]$ which shows the collective opinion of the expert group by $SC-PFWAGA$ the operator:

$$\overline{R_{ij}} = H_{SC-PFWAGA(R_{ij}^1, R_{ij}^2 \dots R_{ij}^k)} \quad (19)$$

.

Step 5. Calculate the three levels of the degree of consensus using Eqs. (6)–(8), and identify the evaluation value with an insufficient consensus degree. If there is a consensus level AUE^h not reached γ, identify the set of APS and continue to step 6. Otherwise, proceed to Step 7.

Step 6. Make consensus adjustments. If (h,i,j) belongs to the set of APS, the corresponding evaluation $R_{ij}^{h,t}$ must be adjusted. Consensus adjustments were made according to the following formula:

$$R_{ij}^{h,t+1} = H_{PFWAGA\left((1-\phi)R_{ij}^{h,t}, \phi \overline{R_{ij}^t}\right)} \quad (20)$$

,

where the adjustment coefficient is used to control the adjustment range $\phi \in (0,1)$. The larger the ϕ, the more different the divergences are inclined to group consensus, and the greater the range of adjustment. Here, t represents rounds of consensus adjustments. Then, repeat Step 5.

Step 7. Perform aggregation. After passing the consensus degree examination, the collective opinions of the experts need to be further aggregated. Based on the group decision matrix $\overline{R_{ij}^T}$ in the final T round, we calculate the final evaluation with criteria weights:

$$R_i^T = H_{PFWAGA(\overline{R_{i1}^T}, \overline{R_{i2}^T}, \dots, \overline{R_{im}^T})} \quad (21)$$

Step 8. Calculate the final score of each scheme and select the optimal scheme.

Step 9. End.

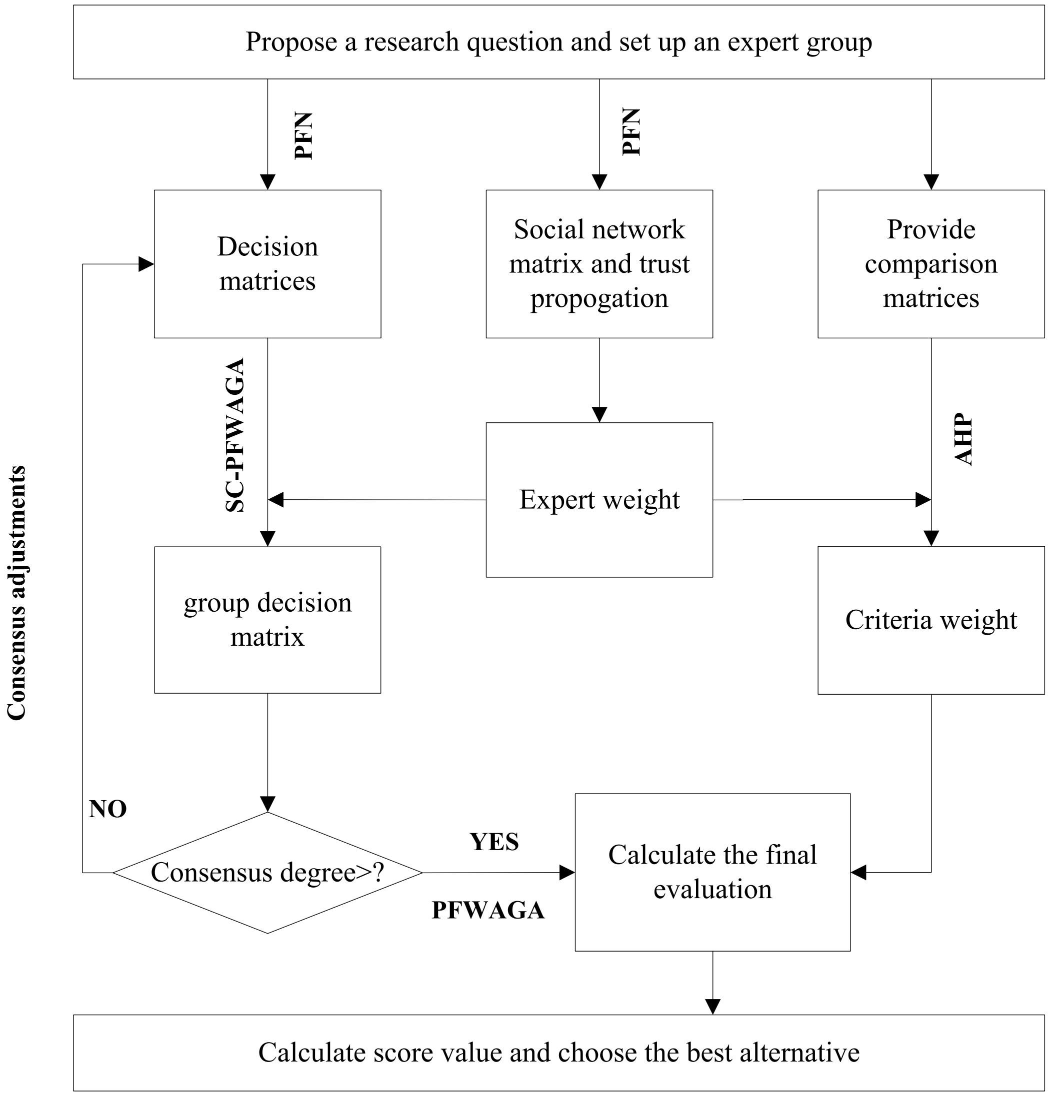


Fig. 2. Flowchart of the proposed method

4. Case study

4.1 Practical problem description

A community has 24,000 residents with 15 high-rise residential buildings, 58 multi-story and small high-rise residences, 30 townhouses, and several supporting sports venues, clubs, shops, and storefront rooms. The community was divided into two phases, and the middle river separated them. Due to the large population of the community, along with the rise of the immediate distribution industry in recent years, daily orders of fresh products in the community have reached hundreds. Thus, delivery staff frequently enter and leave the community, causing many problems:

(1) The community covers a vast area and road conditions are complex, and the

delivery personnel might not be familiar with the location, which affects the delivery efficiency of orders.

(2) In the community, there have been many driving accidents caused by the fast speed of electric vehicle delivery. Allowing electric delivery vehicles to move through residential districts poses a serious safety hazard.

(3) Frequent entry and exit of a large number of distribution personnel are not conducive to epidemic prevention and control, and residents have a high preference for contact-free distribution.

After comprehensive consideration, the community reached a cooperation agreement with a large supermarket chain nearby, planning to use unmanned cars to solve the delivery of all products from the supermarket. Therefore, the leaders of the supermarket and the community sent two people (a total of four people) to form an expert group. The team was required to make a comprehensive evaluation of the five preliminarily selected UGDVs, to select the most suitable one and apply it for future use. The details of alternative unmanned delivery vehicles are as follows:

JD-DIDO (A_1): It has a large capacity grid design, carrying 2.25 m^3, and is a modular design, which can be changed according to different scenes at any time. It is equipped with a laser radar, monocular camera, infrared thermal imager, multi-sensor cooperation, L4-level automatic driving technology, Beidou satellite positioning system, advanced Booster intelligent braking system, and intelligent power supply system to ensure stability and safety of driving.

Meituan “Magic Bag Magic Bag 20” (A_2): It has two crates with a capacity of 0.55 m^3 and can carry up to 150 kg. The speed limit of the delivery vehicle was 20 km/h, with a range of 120 km. The sensing equipment is very rich, with three Lidar, nineteen cameras, two millimeter-wave radars, and nine ultrasonic radars. The vehicle completes the L4 level automatic driving action through its own ability and establishes a fivefold safety guarantee system.

Alibaba “XiaoManLu” (A_3): Its body is $2.1\times0.9\times1.2$ m, which suits narrow roads. It can carry 100 kg and accommodate 50 pieces of regularly sized parcels, with a range of over 100 km. It operates normally in rain and snow, with a pullout battery and easy power change in 20 s. Vehicle sensing equipment includes RoboSense's exclusive radar lidar, circling cameras, millimeter-wave radar, and inertial navigation sensors. To ensure the safety and stability of the vehicle, a fivefold redundancy design was introduced into the system architecture of the robot.

Xingshen Intelligent juedi-3000H (A_4 **)**: Its body is $1.88\times1\times1.77$ m, the container space is 1 m^3, and the maximum load is 500 kg. The container adopts a modular design for withdrawal separation. The vehicle is also equipped with a comprehensive sensing system built with multiple sensors, with "seven layers of sensor protection detection." The delivery time is accurate to minutes, the location is accurate to centimeters, and customers only need to scan the QR code on a mobile phone to order a meal.

White Rhino UGDV (A_5 **)**: The vehicle is 1.0 m wide and 2.5 m long, with a maximum load of 250 kg and a cargo space of 2m^3. The vehicle has a point cloud sensing system based on 3D Lidar and an efficient point cloud matching algorithm, as well as a multi-sensor fusion positioning algorithm that deeply integrates IMU, GNSS, and wheel speed information, enabling accurate positioning and effective decision-making. The vehicle has a security system of multiple safety lines, which can realize the precise calculation of the collision risk at the millisecond level to ensure safety.

The features of five alternatives are shown in Figure 3.

Fig. 3. Images of five alternative UGDVs

4.2 Expert weight

First, the experts use PFNs to express their level of trust in other experts to obtain the original social network matrix A:

$$A=\begin{pmatrix} - & \langle 0.9,0.1\rangle & \langle 0.7,0.3\rangle & - \\ \langle 0.7,0.1\rangle & - & \langle 0.7,0.4\rangle & \langle 0.8,0.1\rangle \\ - & - & - & \langle 0.7,0.2\rangle \\ \langle 0.8,0.3\rangle & - & \langle 0.7,0.2\rangle & - \end{pmatrix}$$

To fully connect the network, two experts without a trust relationship can generate trust through a third party. For example, to propagate the trust relationship between e_1 and e_4, there are two possible indirect paths: $l_1: e_1 \to e_2 \to e_4$, $l_1: e_1 \to e_3 \to e_4$, and the computation involved is

$$\sigma_{14}^{l_1}=\left\langle \frac{0.9\times 0.8}{1+0.1\times 0.2}, \frac{0.1+0.1}{1+0.1\times 0.1} \right\rangle = \langle 0.71,0.20\rangle$$

$$\sigma_{14}^{l_2}=\left\langle \frac{0.7\times 0.7}{1+0.3\times 0.3}, \frac{0.3+0.2}{1+0.3\times 0.2} \right\rangle = \langle 0.45,0.47\rangle$$

$$\sigma_{14}=H_{PFWAGA1(\sigma_{14}^{l_1},\sigma_{14}^{l_2})}=\langle 0.59,0.34\rangle .$$

Therefore, the complete social network trust matrix is

$$A=\begin{pmatrix} - & \langle 0.9,0.1\rangle & \langle 0.7,0.3\rangle & \langle 0.59,0.34\rangle \\ \langle 0.7,0.1\rangle & - & \langle 0.7,0.4\rangle & \langle 0.8,0.1\rangle \\ \langle 0.53,0.47\rangle & \langle 0.45,0.54\rangle & - & \langle 0.7,0.2\rangle \\ \langle 0.8,0.3\rangle & \langle 0.7,0.39\rangle & \langle 0.7,0.2\rangle & - \end{pmatrix}$$

Calculate the TS matrix:

$$TS = \begin{pmatrix} - & 0.8 & 0.4 & 0.23 \\ 0.48 & - & 0.33 & 0.63 \\ 0.06 & -0.09 & - & 0.45 \\ 0.55 & 0.34 & 0.45 & - \end{pmatrix}.$$

Then, the degree to which experts are trusted OT is

$$OT = (1.09, \quad 1.05, \quad 1.18, \quad 1.31).$$

Thus, the final weight of experts is

$$\omega = (0.24, \quad 0.23, \quad 0.25, \quad 0.28).$$

Through social networks and trust propagation, the degree of trust among experts in the group can be objectively and accurately determined, and it can also be converted into expert weights. In this manner, expert weight can reflect the power of discourse within the group. The more trusted the experts, the higher their power of discourse, and thus the greater their weight. This group had e_4, the highest weight.

4.3 Criteria weight

First, w^{group} and w^{local} can be obtained by calculating the comparison matrix for each group of evaluation criteria provided by the experts. For example, Table 3 shows the comparison results of the index in the "Run on the road" part by expert e_1, which obtained $CR = 0.057 < 0.1$ and passed the consistency test. Otherwise, it requires experts to modify it again.

Table 3. Weight of indicators by the AHP method

	R1	R2	R3	R4	$w^{local(R),1}$
R1	1.00	0.50	0.50	1.00	0.16
R2	2.00	1.00	3.00	2.00	0.43
R3	2.00	0.33	1.00	2.00	0.25
R4	1.00	0.50	0.50	1.00	0.16

The local priority weights obtained (Table 3) were $w^{local(R),1} = (0.16, 0.43, 0.25, 0.16)$ e_1

criterion $w^{global,1}$ provided by expert e_1 can be calculated using Eq.(17). Similarly, other experts can provide their criteria weights. Finally, combined with the expert weight, Eq. (18), the final criteria weight is listed in Table 4.

Table 4. Final criteria weight

UGDV Criteria		Local priority		Global priority	
Purchase a vehicle with a risk assessment [Priority: 0.206]					
P1	The initial cost	0.150	(3)	0.031	(12)
P2	Expected security risks	0.457	(1)	0.094	(3)
P3	Emergency capacity	0.403	(2)	0.083	(4)
The online operation [Priority: 0.155]					
O1	Platform docking capability	0.327	(2)	0.051	(10)
O2	Data processing efficiency	0.446	(3)	0.069	(6)
O3	Network Security	0.237	(1)	0.037	(11)
Loading and picking up [Priority: 0.119]					
L1	Delivered payload capability	0.241	(2)	0.029	(13)
L2	Quality of distribution environment	0.578	(1)	0.069	(7)
L3	Human-computer interaction level	0.191	(3)	0.023	(15)
Run on the road [Priority: 0.44]					
R1	Vehicle positioning accuracy	0.126	(4)	0.055	(8)
R2	Environment awareness capability	0.384	(1)	0.169	(1)
R3	Path planning capability	0.329	(2)	0.144	(2)
R4	By - wire control ability	0.172	(3)	0.075	(5)
Complete operation [Priority: 0.091]					
C1	Charging waiting cost	0.163	(3)	0.014	(16)
C2	Operating Cost of Site	0.540	(1)	0.053	(9)
C3	Equipment maintenance and upgrade costs	0.297	(2)	0.024	(14)

As shown in the weight results of the whole indicator system, “Run on the road” is the part most valued by expert group members, with a group priority of 0.44. All four experts chose this part for the first time. Criteria R2, R3, R4, and R1 in the group, rank 1, 2, 5, and 8, with comprehensive weights of 0.169, 0.144, 0.075, and 0.055, respectively. This result indicates that the path driving link is the most important part of the expert group. Further, the core performance of the autonomous driving of the unmanned delivery vehicle is the key to the evaluation of an unmanned delivery vehicle. Among them, environmental awareness ability and path planning ability have the largest weights, which are the core systems of each company and the key to competitiveness.

In the purchase of a vehicle with a risk assessment stage, P_2 and P_3 have the third and fourth highest weights. This indicates that, compared with the price of the unmanned delivery vehicle, experts pay more attention to the risks that may occur in its operation. As the unmanned delivery vehicle is autonomous throughout the driving process, the potential risks and the ability to handle them are crucial. This is not only considering the risk of the transport and distribution vehicle itself but also the impact on surrounding pedestrians and vehicles when driving on the road section.

In the online operation stage, the O_2 score is the highest, and its comprehensive ranking also reaches 0.069 (rank sixth). This indicates that the operation of unmanned distribution vehicles requires good system performance and can handle a large amount of data in the operation process.

In loading and picking up scenarios, the comprehensive weight of L_2 reaches 0.069 (rank seventh). This indicates that, compared with excellent load capacity, whether the unmanned delivery vehicle can cater to diversified distribution environments to meet the special requirements of different products is the focus of the expert group.

4.4 Selection process and results

Each expert presents his/her Pythagorean fuzzy decision matrix $R^h = \left(r_{ij}^h, \mu_{ij}^h\right)_{5\times16}$ $(h = 1,2,3,4)$, where $r_{ij}{}^h = (t_{ij}, f_{ij})$ to represent the evaluation of the expert e^h A_i C_j. All expert evaluation information is provided in the appendix (Tables A1–A4). Based on the individual decision matrix R^h, a collective opinion $\overline{R}$ was computed using Eq. (19) and SC-PFWAGA operator, as shown in Table 5.

Table 5. Group decision matrix for the first round

	A1	A2	A3	A4	A5
P1	<0.69,0.26>	<0.63,0.25>	<0.81,0.21>	<0.42,0.45>	<0.61,0.36>
P2	<0.76,0.26>	<0.55,0.27>	<0.64,0.28>	<0.59,0.42>	<0.6,0.27>
P3	<0.68,0.31>	<0.73,0.23>	<0.8,0.31>	<0.59,0.36>	<0.53,0.22>
O1	<0.51,0.33>	<0.69,0.27>	<0.65,0.44>	<0.48,0.52>	<0.68,0.22>

O2	<0.53,0.34>	<0.58,0.38>	<0.66,0.36>	<0.67,0.26>	<0.53,0.35>
O3	<0.69,0.37>	<0.59,0.23>	<0.72,0.28>	<0.49,0.29>	<0.72,0.26>
L1	<0.58,0.3>	<0.67,0.18>	<0.69,0.31>	<0.59,0.36>	<0.53,0.37>
L2	<0.64,0.39>	<0.68,0.31>	<0.63,0.37>	<0.62,0.32>	<0.5,0.27>
L3	<0.77,0.3>	<0.59,0.27>	<0.7,0.36>	<0.62,0.42>	<0.81,0.31>
R1	<0.71,0.22>	<0.65,0.35>	<0.72,0.26>	<0.55,0.36>	<0.53,0.27>
R2	<0.67,0.3>	<0.62,0.34>	<0.66,0.32>	<0.57,0.3>	<0.69,0.27>
R3	<0.7,0.22>	<0.79,0.17>	<0.63,0.36>	<0.51,0.39>	<0.5,0.4>
R4	<0.6,0.23>	<0.76,0.29>	<0.74,0.34>	<0.58,0.37>	<0.57,0.34>
C1	<0.71,0.33>	<0.54,0.41>	<0.7,0.44>	<0.51,0.44>	<0.8,0.3>
C2	<0.64,0.27>	<0.66,0.31>	<0.67,0.31>	<0.66,0.23>	<0.66,0.19>
C3	<0.58,0.31>	<0.63,0.25>	<0.73,0.32>	<0.42,0.42>	<0.52,0.36>

From Eqs. (6) to (8), the consensus degrees of the four experts were calculated to be $AUE^{1,1}=0.875$, $AUE^{2,1}=0.850$, $AUE^{3,1}=0.838$, and $AUE^{4,1}=0.832$. We set the threshold $\gamma=0.85$. Experts e_3 e_4 need a consensus adjustment. Back to alternative and element level in turn, the APS set is obtained, as shown in Appendix A5. Then, we make consensus adjustments based on the APS. Taking one element $(3,1,1)$ as an example, $CE_{11}^{3}=0.796$, $\mathrm{ACE}_{1}^{3}=0.819$, and $\mathrm{AUE}^{3}=0.796$. The corresponding evaluation $R_{11}^{3}=\langle 0.4,0.3\rangle$ was adjusted by $\overline{R_{11}}=\langle 0.69,0.26\rangle$:

$$R_{11}^{3,2}=H_{PFWAGA1(R_{11}^{3,1},\overline{R}_{11}^{1})}=\langle 0.465,0.292\rangle,$$

where the adjustment coefficient $\phi=0.2$. Other evaluations were adjusted successively in the same manner. After finishing one round of consensus adjustment, a new group decision matrix $\overline{R_{ij}^{2}}$ is computed using $R_{ij}^{h,2}$.

Table 6. Group decision matrix for the second round

	A1	A2	A3	A4	A5
P1	<0.71,0.26>	<0.64,0.24>	<0.81,0.21>	<0.42,0.45>	<0.61,0.36>
P2	<0.76,0.26>	<0.56,0.28>	<0.65,0.29>	<0.59,0.42>	<0.6,0.27>
P3	<0.68,0.31>	<0.75,0.23>	<0.8,0.31>	<0.59,0.36>	<0.53,0.22>
O1	<0.52,0.34>	<0.71,0.27>	<0.66,0.44>	<0.49,0.51>	<0.68,0.22>
O2	<0.55,0.35>	<0.61,0.38>	<0.68,0.35>	<0.67,0.26>	<0.53,0.33>
O3	<0.71,0.38>	<0.6,0.23>	<0.72,0.27>	<0.49,0.29>	<0.72,0.26>
L1	<0.6,0.32>	<0.67,0.18>	<0.69,0.31>	<0.59,0.36>	<0.53,0.36>
L2	<0.63,0.39>	<0.7,0.32>	<0.65,0.36>	<0.62,0.32>	<0.5,0.27>
L3	<0.77,0.3>	<0.62,0.28>	<0.7,0.36>	<0.62,0.42>	<0.81,0.31>

R1	<0.71,0.22>	<0.65,0.36>	<0.74,0.26>	<0.55,0.36>	<0.53,0.27>
R2	<0.67,0.29>	<0.64,0.36>	<0.66,0.34>	<0.57,0.3>	<0.69,0.27>
R3	<0.7,0.22>	<0.79,0.17>	<0.63,0.36>	<0.5,0.39>	<0.49,0.4>
R4	<0.62,0.24>	<0.76,0.3>	<0.74,0.34>	<0.57,0.37>	<0.57,0.33>
C1	<0.71,0.35>	<0.55,0.42>	<0.71,0.44>	<0.51,0.44>	<0.8,0.3>
C2	<0.66,0.26>	<0.69,0.31>	<0.68,0.31>	<0.67,0.22>	<0.65,0.19>
C3	<0.59,0.33>	<0.64,0.24>	<0.73,0.31>	<0.42,0.42>	<0.52,0.36>

In this round, the consensus degree of the four experts was calculated to be $AUE^{1,1} = 0.880$, $AUE^{2,1} = 0.853$, $AUE^{3,1} = 0.853$, and $AUE^{4,1} = 0.856$. Therefore, another round of adjustments is unnecessary. Combined with the criteria weight generated in Section 4.3, the final evaluation of all UGDVs (A_i) can be obtained, a presented in Table 7.

Table 7. Final evaluation results

	A_1	A_2	A_3	A_4	A_5
Result	<0.63,0.29>	<0.67,0.26>	<0.71,0.32>	<0.52,0.36>	<0.51,0.26>

Finally, the score values of the five alternatives were 0.309, 0.386, 0.402, 0.139, and 0.189. The result is $A_4 \prec A_5 \prec A_1 \prec A_2 \prec A_3$, which implies that the best choice is A_3.

Again, if we change the operator to SC-PFWAGA2, the score values are 0.472, 0.541, 0.583, 0.323, and 0.350, which implies that $A_4 \prec A_5 \prec A_1 \prec A_2 \prec A_3$. However, the best option remains A_3.

4.5 Comparison results

To explain the rationality and effectiveness of the SC-PFWAGA operator, the results of other methods, including the PFWAGA, PFGA, and PFWA operators, need to be compared.

Table 8. Ranking results of different operators

Operators	Ranking results

SC-PFWAGA1	$A_4 \prec A_5 \prec A_1 \prec A_2 \prec A_3$
SC-PFWAGA2	$A_4 \prec A_5 \prec A_1 \prec A_2 \prec A_3$
PFWAGA1	$A_4 \prec A_5 \prec A_1 \prec A_2 \prec A_3$
PFWAGA2	$A_4 \prec A_5 \prec A_1 \prec A_2 \prec A_3$
PFWA	$A_4 \prec A_5 \prec A_1 \prec A_2 \prec A_3$
PFGA	$A_4 \prec A_5 \prec A_1 \prec A_3 \prec A_2$

The results presented in Table 8 show that, for the same set of evaluation information, PFWA and PFGA operators obtained different ranking conclusions with low scores. This indicates that differences in weights and expert ratings lead to the possibility of inconsistent results between the two operators. Two types of results for the same group of evaluations make the judgment less accurate and powerful. The results of PFWAGA1 and PFWAGA2 operators are consistent, indicating that the method has a good correction effect on PFWA and PFGA operators. The more stable the result, the more reliable the final ranking obtained. The SC-PFWAGA operator combines the influence of expert confidence level on the basis of the PFWAGA operator and further adjusts some projects with a low degree of expert grasp so that the final results can be more credible. In this case, the expert confidence level did not significantly affect the final assessment and had the same rank.

Table 9. Comparisons with existing methods

Characteristics	Method 1 (Zhang & Hu, 2021)	Method 2 (Zhang, et al, 2020)	This paper
Solve problem	MCDM problem	MCDM problem	MCDM problem
Expert weight	Given by decision makers in advance	Come from social networks	Come from social networks
Trust metric	Non	Based on real numbers from 0 to 1	Pythagorean fuzzy information
Trust propagation	Non	t-norm trust propagation operator	Dual trust propagation operator

Adjust consensus	Non	Non	Three levels of expert consensus

Several studies related to MCDM issues were selected for further comparative analysis, as shown in Table 9. Different solutions could be selected to determine expert weights. Considering that the network relationship between experts can more accurately grasp the voice and status of experts in a group, the proposed expert weight calculation method from the social network is more reliable. Moreover, the decision-making process of this study not only considers the trust network between experts but also chooses the PFS to express and construct the trust matrix more precisely, unlike other methods. Overall, the application of the social network MCDM improves the decision-making results in terms of trust expression, trust dissemination, expert weight determination, and consensus level.

4.6 Sensitivity analysis

To further analyze the final sorting results, in this section, we examine the influence of parameter changes on the aggregation results and then illustrate the comparative analysis among operators from different perspectives.

Fig. 4 shows that the aggregation results of PFWA and PFGA operators may be greatly different and unstable. Conversely, those of the SC-PFWAGA operator are always in the middle of the two results, and different results are biased due to different λ choices. The aggregation scores of PFWA and PAGA operators are 0.253 and -0.162, respectively, with a difference of 0.416. Taking $\lambda = 0.5$ as an example, the aggregation scores achieved by PFWAGA1 is 0.020 and PFWAGA2 is 0.074, with a difference of 0.054. This indicates that the aggregation results are more concentrated and more accurate. If λ is larger, the result is more varied to the PFWA approach; however, if λ is smaller, the result is more biased to the PFGA operator. With the increase of λ, the variation trend of the aggregation results of C-PFWAGA1 and SC-PFWAGA2 operators is also different.

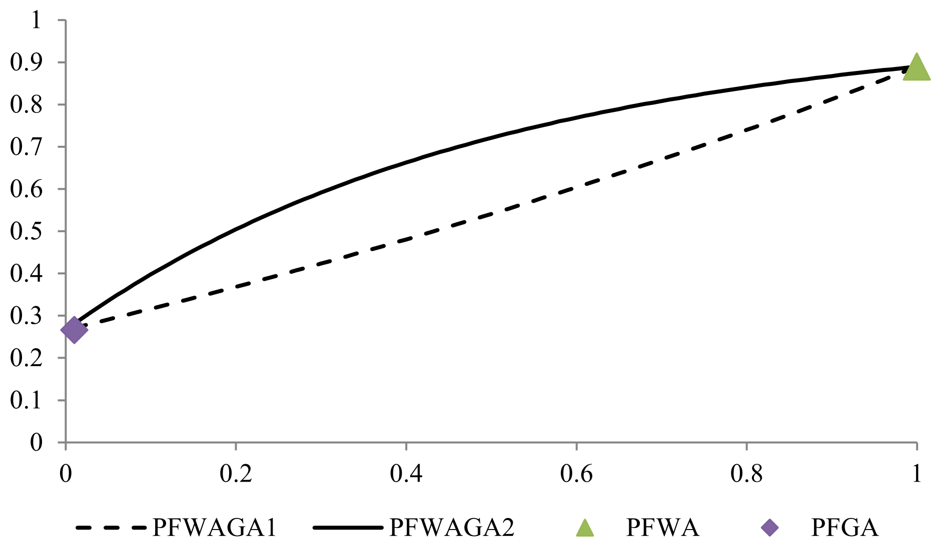


Fig. 4. Comparison of the aggregation results of the four operators.

As shown in Figs. 5 and 6, with the change in parameter λ, the scores and rankings of all alternatives are relatively stable. At around $\lambda = 0.7$, the ranking of A_2 and A_3 changed. This indicates that the convergence of the PFWA and PFGA operators results in unstable results. It can be observed that both PFWAGA1 and PFWAGA2 can achieve a relatively stable and accurate position in the results, with clear differences. This result is more reliable than that of PFWA and PFGA operators.

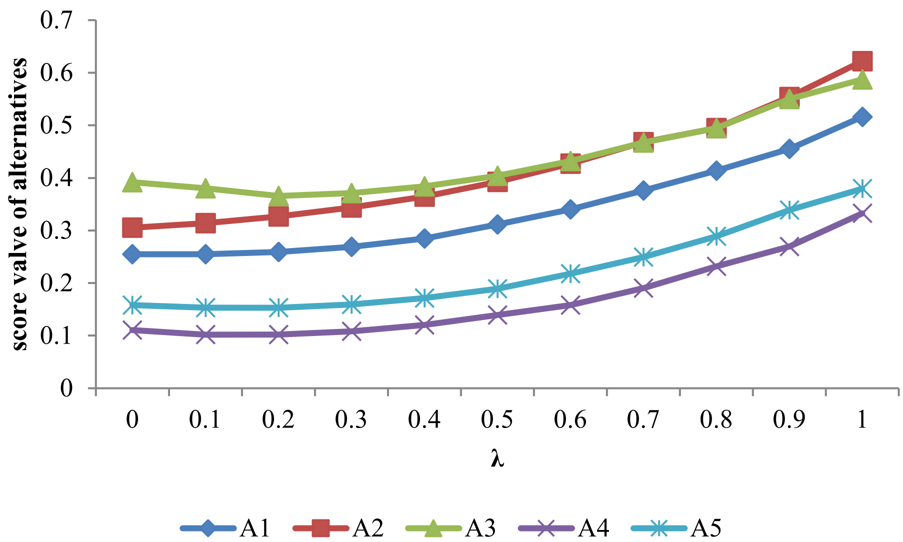


Fig. 5. Results of the PFWAGA1 operator with different values of λ.

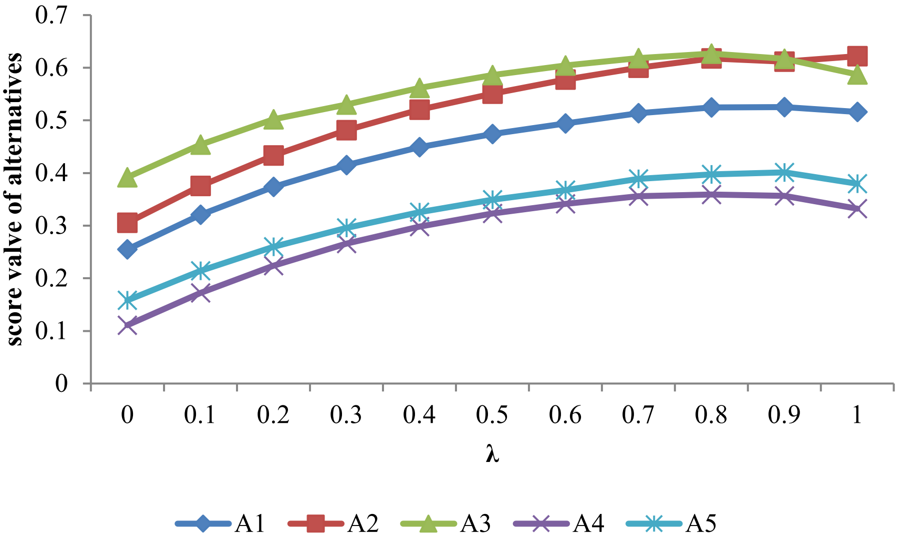


Fig. 6. Results of the PFWAGA2 operator with different values of λ.

Fig. 7 shows the analysis of the impact of expert confidence on the final results. We set two experts with a higher evaluation PFN $\langle 0.9, 0.1 \rangle$ and a lower evaluation value $\langle 0.6, 0.4 \rangle$. In the case that they all have a weight of 0.5, if they all have sufficient confidence in the evaluation, the final evaluation score is 0.529, as shown in the rhombic marker. If one person has low self-confidence, the final result will be closer to the other expert's judgment. This is also in line with the need for real-world decision-making that more weight is given to more assured expert.

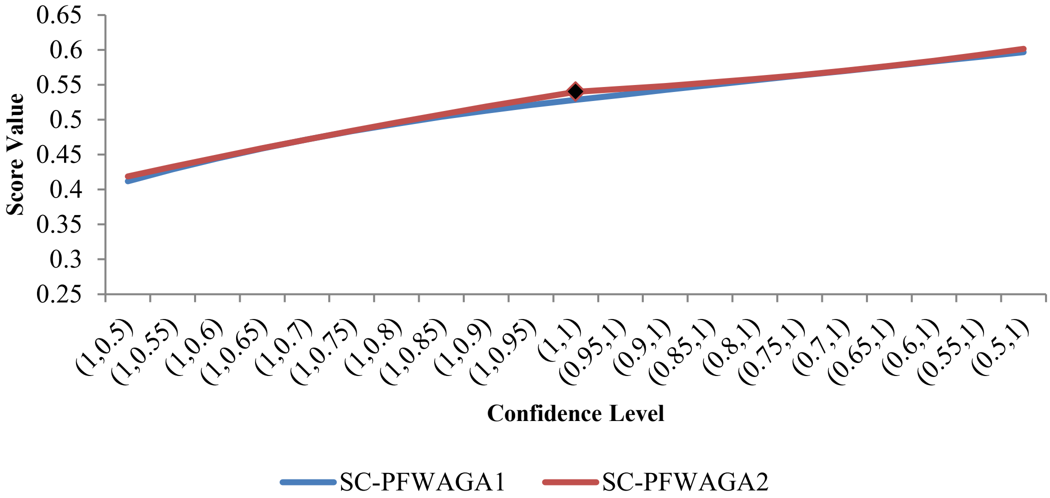


Fig. 7. Aggregation result of the SC-PFWAGA operator with confidence level.

5. Policy implications

Based on the conclusions of this study, the following suggestions are proposed:

(1) Encourage technological innovation and preliminary technical planning (Zhang et al., 2016). As the four experts provide the maximum weight of "Run on the road," the most important aspect for UGDVs is their core intelligent technology. Therefore, the government should encourage technological innovation, increase funding, and policy support for technological research of relevant enterprises. Further, advanced foreign technology should be introduced in key areas of unmanned vehicles, and the core competitiveness of domestic autonomous vehicles must be enhanced. By doing a good job of related supporting content, such as technical personnel training and planning of unmanned vehicle operation sites, the upstream and downstream of the entire unmanned distribution industry can develop together in a coordinated way and drive the overall development of the entire industry.

(2) The corresponding traffic legal system of UGDVs must be improved. UGDVs are a key link in the construction of smart cities and involves many sectors. After technical problems are addressed, the promotion of UGDVs might conflict with existing construction modes (Mark, 2020). At present, no planning system conducive to the development of unmanned distribution has been developed. In the future, urban planning and community construction should consider the development of unmanned distribution systems. Collaboration around automation is a field where roles and responsibilities are reshaped in relation to smart mobility (Oldbury & Isaksson, 2021).

(3) Expansion of application scenarios for unmanned delivery vehicles (e.g., UGDV) has been useful in the transportation of food, medicine, and other products. However, expanding its application potential and distribution products remains necessary. For example, launching customized UGDVs for cities with special terrain and climate or cooperating with delivery robots to wait for door-to-door delivery are also necessary.

6. Conclusion

UGDVs play an increasingly important role in alleviating urban distribution pressure and assisting transportation in dangerous scenarios, showing a significant market application prospect. In the future, especially in the field of community delivery, UGDVs show a great potential. Thus, this study proposed an effective social network MCDM model to solve the selection of community UGDVs and helped improve the knowledge system on UGDVs in the following aspects. (1) A complete criteria evaluation system of the UGDV was proposed, which was significant for its improvement and development, and helpful for decision-makers in realizing effective evaluation. The system can promote better applications of UGDVs and provide better play to the potential of these vehicles in future smart city construction. (2) Addressed uncertain information in the UGDV evaluation process using a Pythagorean fuzzy tool to handle the complexity. Moreover, this study innovatively proposed SC-PFWAGA1 and SC-PFWAGA2 operators, which overcome some defects of the original operators and filled in the gaps of the vague study of the PFS. (3) Made the UGDV evaluation process more reasonable through a combination of social network and fuzzy evaluation theory, and thus enabling the evaluation results to better reflect the actual situation. In addition, this study defined two limited weight levels and combined AHP to calculate the weight of indicators hierarchically. Concurrently, consensus adjustment has ensured the consistency of the overall opinions of experts. Thus, the proposed MCDM method is crucial to the practical applications of UGDVs, theoretical content of the PFS, and extended applications of the social network analysis.

However, the proposed approach has some limitations. Expert social networks mainly rely on subjective opinions in the example. Objective factors can be considered when constructing expert networks to improve the application mode of social networks in the MCDM. Further, we can continue to improve effective aggregation methods by extending it to the interval Pythagorean environment or by adding new properties. In addition, finding a more reasonable and realistic weight determination method that can be used to solve complex problems in many fields is possible.

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Appendix:

Table A1. Evaluation matrix R^1 of expert e_1

	A1	A2	A3	A4	A5
P1	(<0.9,0.1>,0.9)	(<0.8,0.1>,1)	(<0.8,0.1>,0.9)	(<0.6,0.3>,0.8)	(<0.6,0.3>,0.9)
P2	(<0.9,0.1>,0.7)	(<0.6,0.4>,0.7)	(<0.8,0.1>,0.6)	(<0.6,0.6>,0.7)	(<0.8,0.2>,0.8)
P3	(<0.8,0.4>,0.7)	(<0.9,0.1>,0.9)	(<0.9,0.2>,0.9)	(<0.6,0.5>,0.9)	(<0.7,0.1>,0.7)
O1	(<0.6,0.5>,0.9)	(<0.9,0.1>,0.7)	(<0.6,0.6>,0.7)	(<0.6,0.6>,0.8)	(<0.8,0.1>,1)
O2	(<0.8,0.3>,0.6)	(<0.8,0.3>,0.7)	(<0.9,0.2>,0.8)	(<0.7,0.2>,0.9)	(<0.6,0.4>,0.7)
O3	(<0.9,0.3>,0.7)	(<0.6,0.2>,0.9)	(<0.6,0.1>,0.9)	(<0.6,0.1>,0.7)	(<0.9,0.2>,0.6)
L1	(<0.7,0.5>,0.8)	(<0.6,0.2>,1)	(<0.6,0.2>,0.7)	(<0.8,0.4>,0.7)	(<0.6,0.3>,0.8)
L2	(<0.6,0.5>,0.6)	(<0.8,0.3>,0.8)	(<0.8,0.3>,0.7)	(<0.9,0.2>,0.8)	(<0.6,0.3>,0.9)
L3	(<0.9,0.2>,0.7)	(<0.7,0.4>,0.7)	(<0.6,0.3>,0.9)	(<0.9,0.3>,0.9)	(<0.9,0.2>,0.9)
R1	(<0.9,0.2>,0.9)	(<0.7,0.3>,0.9)	(<0.9,0.1>,0.7)	(<0.8,0.2>,0.8)	(<0.6,0.3>,0.7)
R2	(<0.8,0.3>,0.9)	(<0.9,0.3>,0.7)	(<0.8,0.4>,0.8)	(<0.8,0.2>,0.8)	(<0.9,0.2>,0.7)
R3	(<0.8,0.1>,1)	(<0.9,0.1>,0.9)	(<0.7,0.2>,1)	(<0.7,0.5>,0.9)	(<0.7,0.3>,0.7)
R4	(<0.7,0.2>,0.8)	(<0.7,0.5>,0.8)	(<0.8,0.4>,0.9)	(<0.6,0.5>,0.8)	(<0.6,0.3>,0.7)
C1	(<0.6,0.5>,0.6)	(<0.6,0.5>,0.8)	(<0.8,0.4>,0.9)	(<0.8,0.4>,0.7)	(<0.8,0.2>,1)
C2	(<0.6,0.1>,0.9)	(<0.9,0.2>,1)	(<0.6,0.2>,0.8)	(<0.9,0.2>,0.9)	(<0.8,0.1>,0.8)
C3	(<0.7,0.4>,0.9)	(<0.6,0.2>,0.9)	(<0.6,0.1>,0.8)	(<0.6,0.2>,0.8)	(<0.6,0.3>,0.9)

Table A2. Evaluation matrix R^2 of expert e_2

	A1	A2	A3	A4	A5
P1	(<0.8,0.2>,0.8)	(<0.6,0.1>,0.7)	(<0.8,0.1>,0.8)	(<0.2,0.3>,0.8)	(<0.4,0.3>,0.7)
P2	(<0.8,0.1>,0.8)	(<0.6,0.1>,0.9)	(<0.7,0.3>,0.9)	(<0.2,0.3>,0.6)	(<0.3,0.3>,0.8)
P3	(<0.7,0.2>,0.9)	(<0.9,0.1>,0.8)	(<0.9,0.1>,0.7)	(<0.6,0.1>,0.7)	(<0.5,0.1>,0.9)
O1	(<0.6,0.1>,0.7)	(<0.9,0.1>,0.7)	(<0.9,0.1>,0.7)	(<0.4,0.2>,0.7)	(<0.7,0.1>,0.8)
O2	(<0.7,0.3>,0.7)	(<0.8,0.2>,0.7)	(<0.6,0.2>,0.9)	(<0.5,0.1>,0.7)	(<0.3,0.1>,0.8)
O3	(<0.8,0.2>,0.7)	(<0.7,0.1>,1)	(<0.8,0.2>,0.9)	(<0.3,0.3>,0.9)	(<0.2,0.1>,0.8)
L1	(<0.7,0.2>,1)	(<0.7,0.1>,1)	(<0.7,0.1>,0.8)	(<0.5,0.2>,0.7)	(<0.4,0.1>,0.9)
L2	(<0.7,0.2>,0.8)	(<0.9,0.2>,0.7)	(<0.8,0.2>,0.9)	(<0.3,0.3>,1)	(<0.4,0.1>,0.9)
L3	(<0.8,0.2>,1)	(<0.9,0.1>,0.8)	(<0.8,0.2>,0.8)	(<0.2,0.2>,0.7)	(<0.7,0.2>,0.6)
R1	(<0.7,0.1>,1)	(<0.7,0.3>,0.7)	(<0.9,0.2>,0.9)	(<0.3,0.2>,0.8)	(<0.6,0.2>,0.9)
R2	(<0.7,0.1>,0.9)	(<0.6,0.4>,0.8)	(<0.7,0.3>,0.7)	(<0.2,0.2>,0.9)	(<0.7,0.2>,0.9)
R3	(<0.8,0.1>,0.7)	(<0.9,0.1>,0.8)	(<0.6,0.4>,0.8)	(<0.4,0.3>,0.8)	(<0.2,0.3>,0.9)
R4	(<0.8,0.1>,0.6)	(<0.9,0.1>,0.9)	(<0.8,0.1>,0.6)	(<0.3,0.2>,0.7)	(<0.4,0.1>,0.7)
C1	(<0.8,0.2>,0.9)	(<0.7,0.2>,0.7)	(<0.9,0.2>,0.6)	(<0.2,0.3>,0.9)	(<0.7,0.2>,0.7)
C2	(<0.9,0.1>,1)	(<0.8,0.2>,0.5)	(<0.7,0.2>,0.6)	(<0.4,0.7>,0.9)	(<0.5,0.2>,0.6)
C3	(<0.9,0.2>,0.9)	(<0.7,0.1>,0.7)	(<0.8,0.2>,0.9)	(<0.5,0.4>,0.9)	(<0.4,0.3>,1)

Table A3. Evaluation matrix R^3 of expert e_3

	A1	A2	A3	A4	A5
P1	(<0.4,0.3>,0.8)	(<0.4,0.2>,0.7)	(<0.9,0.2>,0.8)	(<0.3,0.6>,1)	(<0.7,0.2>,0.8)
P2	(<0.6,0.3>,0.8)	(<0.2,0.1>,0.7)	(<0.4,0.1>,0.6)	(<0.7,0.2>,1)	(<0.6,0.1>,0.8)
P3	(<0.6,0.2>,1)	(<0.3,0.3>,0.8)	(<0.7,0.4>,0.8)	(<0.6,0.2>,0.6)	(<0.3,0.2>,0.8)
O1	(<0.4,0.1>,0.8)	(<0.4,0.3>,0.9)	(<0.3,0.4>,0.7)	(<0.3,0.6>,0.6)	(<0.6,0.3>,0.8)
O2	(<0.3,0.1>,1)	(<0.3,0.2>,0.7)	(<0.3,0.5>,0.9)	(<0.8,0.2>,0.7)	(<0.7,0.1>,0.9)
O3	(<0.3,0.3>,0.7)	(<0.3,0.2>,0.7)	(<0.9,0.1>,0.7)	(<0.4,0.2>,0.7)	(<0.9,0.2>,0.9)
L1	(<0.3,0.1>,0.9)	(<0.7,0.1>,0.9)	(<0.8,0.4>,0.9)	(<0.5,0.2>,0.7)	(<0.6,0.4>,0.6)
L2	(<0.5,0.3>,0.8)	(<0.3,0.1>,0.8)	(<0.4,0.2>,0.7)	(<0.6,0.3>,1)	(<0.3,0.2>,0.7)
L3	(<0.6,0.3>,0.9)	(<0.2,0.1>,0.9)	(<0.6,0.4>,0.8)	(<0.4,0.6>,0.9)	(<0.9,0.3>,0.9)
R1	(<0.5,0.2>,0.9)	(<0.5,0.2>,0.7)	(<0.4,0.1>,0.7)	(<0.3,0.5>,0.7)	(<0.4,0.1>,0.8)
R2	(<0.6,0.1>,0.7)	(<0.2,0.1>,0.7)	(<0.5,0.1>,0.9)	(<0.6,0.3>,0.9)	(<0.4,0.2>,0.9)
R3	(<0.5,0.2>,0.7)	(<0.6,0.1>,0.9)	(<0.6,0.2>,0.6)	(<0.3,0.2>,0.8)	(<0.3,0.4>,0.8)
R4	(<0.3,0.1>,0.9)	(<0.6,0.1>,0.7)	(<0.7,0.3>,0.9)	(<0.6,0.2>,0.8)	(<0.5,0.3>,0.6)
C1	(<0.7,0.1>,0.7)	(<0.2,0.3>,0.7)	(<0.3,0.5>,0.7)	(<0.4,0.4>,1)	(<0.9,0.3>,0.9)
C2	(<0.3,0.3>,0.9)	(<0.4,0.1>,0.7)	(<0.7,0.2>,0.7)	(<0.5,0.1>,0.9)	(<0.8,0.1>,1)
C3	(<0.3,0.1>,0.7)	(<0.7,0.1>,0.8)	(<0.9,0.3>,0.8)	(<0.3,0.6>,1)	(<0.4,0.3>,0.9)

Table A4. Evaluation matrix R^4 of expert e_4

	A1	A2	A3	A4	A5
P1	(<0.3,0.3>,0.9)	(<0.6,0.5>,0.7)	(<0.8,0.3>,0.7)	(<0.6,0.2>,0.6)	(<0.7,0.5>,0.7)
P2	(<0.9,0.1>,0.7)	(<0.9,0.2>,0.7)	(<0.6,0.3>,0.6)	(<0.7,0.5>,0.7)	(<0.7,0.1>,0.9)
P3	(<0.6,0.3>,0.6)	(<0.6,0.1>,0.9)	(<0.5,0.2>,0.8)	(<0.5,0.3>,0.7)	(<0.8,0.1>,0.9)
O1	(<0.3,0.5>,0.9)	(<0.4,0.4>,0.7)	(<0.7,0.5>,0.8)	(<0.6,0.1>,1)	(<0.3,0.2>,0.7)
O2	(<0.3,0.6>,1)	(<0.3,0.6>,0.7)	(<0.9,0.3>,0.8)	(<0.7,0.1>,0.8)	(<0.4,0.7>,0.9)
O3	(<0.7,0.4>,1)	(<0.8,0.2>,0.9)	(<0.5,0.6>,0.7)	(<0.7,0.3>,1)	(<0.9,0.3>,0.7)
L1	(<0.7,0.1>,0.8)	(<0.8,0.2>,0.9)	(<0.5,0.2>,0.7)	(<0.3,0.2>,1)	(<0.5,0.6>,0.6)
L2	(<0.9,0.2>,0.7)	(<0.7,0.5>,0.9)	(<0.4,0.6>,0.8)	(<0.4,0.1>,0.9)	(<0.9,0.1>,0.7)
L3	(<0.9,0.2>,1)	(<0.4,0.4>,0.7)	(<0.9,0.3>,0.9)	(<0.9,0.2>,0.8)	(<0.5,0.2>,0.7)
R1	(<0.6,0.3>,0.9)	(<0.7,0.4>,0.7)	(<0.5,0.5>,0.7)	(<0.7,0.3>,0.8)	(<0.3,0.1>,0.7)
R2	(<0.5,0.6>,0.6)	(<0.7,0.2>,1)	(<0.6,0.1>,0.8)	(<0.7,0.3>,0.7)	(<0.9,0.2>,1)
R3	(<0.6,0.3>,0.8)	(<0.8,0.2>,0.8)	(<0.6,0.5>,0.8)	(<0.4,0.1>,0.6)	(<0.8,0.4>,0.7)
R4	(<0.8,0.1>,0.7)	(<0.9,0.2>,0.8)	(<0.7,0.2>,0.7)	(<0.9,0.2>,0.7)	(<0.9,0.2>,0.9)
C1	(<0.8,0.3>,0.9)	(<0.6,0.4>,0.8)	(<0.8,0.3>,0.8)	(<0.6,0.6>,0.9)	(<0.9,0.1>,1)
C2	(<0.7,0.4>,0.9)	(<0.3,0.6>,0.7)	(<0.3,0.3>,0.7)	(<0.3,0.5>,0.7)	(<0.9,0.3>,0.7)
C3	(<0.8,0.1>,0.8)	(<0.4,0.4>,0.8)	(<0.9,0.1>,0.6)	(<0.4,0.4>,0.8)	(<0.7,0.4>,1)

Table A5. APS

(3,1,1)	(3,2,3)	(3,3,2)	(4,1,5)	(4,2,9)	(4,3,16)	(4,5,5)

(3,1,4)	(3,2,4)	(3,3,4)	(4,1,7)	(4,2,15)	(4,4,1)	(4,5,7)
(3,1,5)	(3,2,5)	(3,3,5)	(4,1,8)	(4,2,16)	(4,4,4)	(4,5,8)
(3,1,6)	(3,2,6)	(3,3,6)	(4,1,11)	(4,3,3)	(4,4,7)	(4,5,9)
(3,1,7)	(3,2,8)	(3,3,8)	(4,1,13)	(4,3,5)	(4,4,8)	(4,5,10)
(3,1,13)	(3,2,9)	(3,3,10)	(4,1,16)	(4,3,6)	(4,4,9)	(4,5,11)
(3,1,14)	(3,2,10)	(3,3,11)	(4,2,1)	(4,3,7)	(4,4,12)	(4,5,12)
(3,1,15)	(3,2,11)	(3,3,14)	(4,2,2)	(4,3,8)	(4,4,13)	(4,5,13)
(3,1,16)	(3,2,13)	(4,1,1)	(4,2,4)	(4,3,10)	(4,4,15)	(4,5,14)
(3,2,1)	(3,2,14)	(4,1,2)	(4,2,5)	(4,3,11)	(4,5,3)	(4,5,15)
(3,2,2)	(3,2,15)	(4,1,4)	(4,2,6)	(4,3,15)	(4,5,4)	