

A NOVEL DECISION-MAKING FRAMEWORK BASED ON PROBABILISTIC LINGUISTIC TERM SET FOR SELECTING SUSTAINABLE SUPPLIER CONSIDERING SOCIAL CREDIT

Yuanxiang DONG^{1,2}, Xumei ZHENG³, Zeshui XU^{2*}, Weijie CHEN⁴, Hongbo SHI⁵, Ke GONG⁶

¹School of Economics and Management, Taiyuan University of Technology, 030024 Taiyuan, China ²State Key Laboratory of Hydraulics and Mountain River Engineering, Business School, Sichuan University, 610064 Chengdu, China

³School of Management Science and Engineering, Shanxi University of Finance and Economics, 030006 Taiyuan, China

⁴School of Economics and Management, Chongqing Normal University, 400047 Chongqing, China ⁵College of Information, Shanxi University of Finance and Economics, 030006 Taiyuan, China ⁶School of Economics and Management, Chongqing Jiaotong University, 400074 Chongqing, China

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Abstract. Sustainable supplier selection (SSS) has become an essential task for decision-makers in competitive environments. We construct a new decision-making framework for SSS. First, classical SSS usually includes fixed factors in environmental, social and economic dimensions. Differently, we adopt new social factors from credit perspective with corporate social credit system being promoted vigorously by the Chinese government. Next, we employ probabilistic linguistic term sets (PLTSs) to collect experts' judgments about interactive influence between factors. Third, we combine PLTSs with Decision Making Trial and Evaluation Laboratory (DEMATEL) method to identify critical success factors (CSFs) for improving decision-making efficiency. And we also give definition to relative importance degree, standard relative importance degree, deviation of importance degree and influence degree to reflect the interactive influence between factors. To eliminate subjective influence, we combine entropy weighting approach and DEMATEL to compute weights. Fourthly, we redefine dominance degree and apply it into TODIM method for SSS. Finally, the proposed decision-making framework's effectiveness is verified by using the case study of a new energy vehicle (NEV) company. Based on this, sensitivity analysis and comparison of methods are conducted. The results verify that the decision-making framework is valid and effective for SSS.

Keywords: sustainable supplier selection, social credit, probabilistic linguistic term sets, critical success factors, DEMATEL, TODIM.

JEL Classification: C43, C61, D81, M11, Q56.

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*Corresponding author. E-mail: xuzeshui@263.net

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Introduction

Supplier selection is a vital step in enterprise supply chain management (SCM) (Daultani et al., 2019). In response to the growing importance of environmental and social issues, Bai and Sarkis (2010) first proposed a sustainable concept for supplier selection based on triple bottom line (TBL) theory (Elkington, 1998). Sustainable supplier selection (SSS) can reduce environmental pollution and fuel consumption (Cuthbertson et al., 2011; Kannan et al., 2020). Increasing global awareness of environmental protection and policy pressures have driven enterprises to move towards SSS (Garg et al., 2017; Parajuli et al., 2019). Thus, SSS has become a focus for researchers and business managers.

SSS have evolved from green supplier selection. Selecting green suppliers considers both economic and environmental dimensions (Ahi & Searcy, 2013; Mi et al., 2020; Lei et al., 2020b; Wei et al., 2019; Wei et al., 2021a). The economic dimension generally includes quality, cost, distribution, and technology (Wisner et al., 2014; Haeri & Rezaei, 2019). The environmental dimension generally includes fuel, pollution, and ecological technology (Igarashi et al., 2013; Rashidi & Cullinane, 2019). In contrast with the economic and environmental dimensions adopted in green supplier selection, the emergence of TBL theory (Elkington, 1998) has increasingly drawn attention to the social dimension (Seuring & Müller, 2008). Further, social dimensions have been added in recent research on SSS because social factors largely support enterprises' sustainable development (Szegedi & Kerekes, 2012; Busse et al., 2016; Liu et al., 2019c). The social dimension usually involves worker dismissal processes and employee rights, safety, and welfare (Govindan et al., 2013; Blome et al., 2014; Luthra et al., 2017). It's worth noting that the establishment of a social credit system has become an important policy in China since 2002 (The State Council, 2017). A Chinese corporate social responsibility summit forum in 2019 also stressed that social credit has become a crucial factor for enterprises' sustainable development (Ministry of Commerce of the People's Republic of China, 2019; Song et al., 2017). This makes it necessary to consider credit when constructing comprehensive factor system to SSS.

Realistically, SSS involves significant ambiguity and fuzziness (Fallahpour et al., 2017; Lin et al., 2018a; Peng et al., 2020), because of variabilities in the external environment and preferences expressed by experts during evaluation process (Zhang et al., 2017). In recent years, the research methods of SSS based on fuzzy set and its extension theories have developed rapidly. Hoseini et al. (2020) presented a model based on Fuzzy set considering the probabilities to select the supplier with the sustainability criteria. Because intuitionistic fuzzy set has efficacy in representing uncertainty and vagueness in membership, non-membership and hesitancy values, Phochanikorn and Tan (2019) proposed the model for SSS under an intuitionistic fuzzy environment. To address strong fuzziness, ambiguity and inexactness during the evaluation process, interval-valued fuzzy sets (Foroozesh et al., 2018), interval-valued Pythagorean fuzzy sets (Yu et al., 2019), interval type-2 fuzzy sets (Alk, 2020), and interval type-2 trapezoidal fuzzy sets (Hendiani et al., 2020) were employed for SSS.

Further, as most cases of SSS involves many factors, many scholars have proposed integrated SSS models, composed of fuzzy set and classical multi-attribute decision making (MADM) methods, for instance, fuzzy TOPSIS, fuzzy VIKOR, and fuzzy PROMETHEE (Senvar et al., 2014; Fallahpour et al., 2017; Yu et al., 2017; Zhou & Xu, 2018; Banaeian et al., 2018). But in fact, experts do not always precisely express their opinions in quantitative terms and tend to use linguistic information to make evaluation (Xu, 2007). As such, scholars have introduced decision-making methods based on linguistic information and extended it into SSS. Liu et al. (2019b) constructed a new integrated MCDM model for SSS under interval-valued intuitionistic uncertain linguistic environment. Liao et al. (2020) put forward a method for SSS based on hesitant fuzzy linguistic term set. As the extension of the hesitant fuzzy linguistic term set, probabilistic linguistic term set (PLTS) (Pang et al., 2016) not only contains different linguistic terms but also can express the probability information of each linguistic term. Therefore, Song and Li (2019) presented a large-scale group decision-making with incomplete multi-granular probabilistic linguistic term sets and its application in SSS.

However, three problems have emerged with respect to previous SSS models. First, these studies applied the existing factors to SSS, but didn't identify critical success factors (CSFs) (Sahu et al., 2016; Zimmer et al., 2016; Arabsheybani et al., 2018), this may lead to wasted resources and complexity in the subsequent decision-making process. Second, most MADM methods adopt subjective weights by using AHP, ANP methods (Kaur et al., 2014; Yu et al., 2019; Jabbar et al., 2019; Chen et al., 2018). This leads to the deviation of decision result from reality and increase the limitation of decision-making. Third, most decision-making methods do not consider the psychological changes of decision makers (Liu et al., 2019b; Erfan et al., 2019; Negash et al., 2020), which could lead to unpractical results.

To address the problems above, we construct a new decision-making framework including the following improvements. First, we reconstruct the factor system according to the background of Chinese vigorous credit system construction and innovatively add credit factors to select sustainable suppliers. Social factors are identified from the perspective of credit. Second, the new decision-making framework adopts PLTSs to manifest experts' preferences during the evaluation process. Assigning different probability values to linguistic terms, enabling PLTS to effectively express information compared with linguistic term set (LTS) as well as numerical expression, and increasing the precision of decision-making. Third, to simplify the decision-making process and reflect the interactive influence of factors, we combine PLTSs with DEMATEL to solve the problem of CSFs' identification in uncertain environment. At the same time, the expert's preference information on factors is reflected. We also propose the concepts of relative importance degree, standard relative importance degree, deviation of importance degree, and influence degree. These describe the interactive influence between factors. Take both subjective and objective aspects into consideration, then we combine entropy weighting approach and DEMATEL to acquire CSFs' weight. Fourth, to fully consider the psychological state of experts, we adopt TODIM, on the basis of prospect theory, as the preliminary decision-making method to make SSS. We also redefine the dominance degree based on the standard relative importance degree and comparison laws. According to the new dominance degree, we adopt TODIM method to construct new framework for making SSS. Finally, to present the proposed method's effectiveness, the proposed framework is applied in a case study involving a Chinese new energy vehicles (NEVs) company planning to make SSS.

The rest of this article is composed as follows: Section 1 explains the SSS's factors from the perspective of economic, environmental and social credit. Section 2 introduces the mathematical preliminaries, and the proposed decision-making framework is introduced in Section 3. In Section 4, we adopt a case study to verify the proposed method's effectiveness, focusing on making SSS in a Chinese NEV company. Section 5 presents discussions about the new framework. The last Section concludes.

1. Sustainable supplier selection factors

Establishing a suitable SSS factor system can be seen as an essential step to get the optimal supplier. Previous studies about supplier selection mainly payed attention to the economic and environmental these two dimensions (Ahi & Searcy, 2013; Graham et al., 2015). The occurrence of triple bottom line (TBL) theory indicates the beginning of SSS development. TBL theory includes economic, environmental, and social dimensions, among which the social dimension received the most attention until recent years (Bai & Sarkis, 2010; Zimmer et al., 2016). Gradually, more researchers agree that the factors for SSS should focus on three dimensions comprehensively: economic, environmental, and social (Seuring & Müller, 2008; Fallahpour et al., 2017; Gören, 2018; Yu et al., 2019). The existing studies emphasized that enterprises should engage in social responsibility to achieve sustainable development (Szegedi & Kerekes, 2012). China has widely focused on constructing credit system and promulgating credit policies to promote the sustainable development of enterprises (The State Council, 2021). The level of sustainable development in enterprises is evaluated by considering environmental implementation, tax implementation, and quality implementation. However, the existed factors have not been able to fully tally the enterprises' implementation capacity, making it less effective for SSS.

We establish a new factor system, which adopts several social factors from the perspective of credit innovatively. According to previous studies, economic and environmental factors are reorganized and details can be seen in Table 1. Innovative social factors are extracted from relevant policies, which are shown in Table 2. Table 1 and Table 2 are followed by a more detailed explanation of factors, which is shown in Table 3.

1.1. Economic

 κ_1 : Technology capability. Wilson et al. (1994) considered technology capability to be popular economic factor. Chen (2011) noted that technology can play an essential role during SSS, as technology will drive economic development to realize sustainable economic development.

 κ_2 : Confidence in a durable product. A successful sustainable product service system should take sustainability into account to extend the product lifecycle (Khan et al., 2018). Liu et al. (2019a) posited that durable products enable society to establish a new ecosystem of sustainable development. This requires the supplier to provide products of reliable quality and a long life cycle.

 κ_3 : Price of products. Weber et al. (1991) reviewed literature for assessing the criterion most frequently used to select suppliers. From the perspective of sustainable development, product

price is an important factor (Khoshfetrat et al., 2020). Reasonable prices can meet the needs of most consumers, and can attract and retain consumers to achieve sustainable development.

 κ_4 : Financial capability. The financial stability of suppliers directly affects sustainability (Amindoust et al., 2012). It is the underlying premise and guarantee that supports all other activities. Girubha et al. (2016) focused on financial capability as a factor in studying SSS. Financial capability status is critical in evaluating suppliers.

 κ_5 : Increase in supply flexibility. Chaharsooghi and Ashrafi (2014) addressed supply flexibility, which has a great influence on economic development. Organizations benefit from increasing their supply flexibilities to respond to manufacturing schedule fluctuations, demand volatility, and forecast accuracy (Li et al., 2019).

1.2. Environmental

 κ_6 : Energy usage. Energy usage is linked to achieving supplier environmental goals (Neumüller et al., 2016). To increase the utilization rate of new energy and to alleviate pollution problems, the Chinese government proposed a range of policies related to new energy development (Lin et al., 2018b). The rational use of energy can reduce pollution and realize the long-term development of suppliers.

 κ_7 : Pollution reduction. Pollution reduction is a fundamental factor in an enterprise to meet ecological standards (Jia et al., 2015; Hou et al., 2020). Memari et al. (2019) considered how the pollution reduction criterion related to reducing the amount of supplier's greenhouse gas emissions to align them with regional and international ecological policies.

 κ_8 : Environmental skill. Environmental skill can be an effective way to attain green production, increasing environmental performance (Fallahpour et al., 2017). Because environmental technology allows suppliers to reduce pollutant emissions, Liu et al. (2019a) considered environmental skills in SSS.

Perspective	Sub-Criterion	Application	Journal	Author
Economic	Technology capability Confidence in a durable product Price of products Financial capability Increase of supply flexibility	Supplier selection NEVs Automotive industry Supplier selection Supply chain management	Information Science Journal of Cleaner Production Engineering Optimization Applied Soft Computing Journal of Cleaner Production	Chen et al. Liu et al. Sahar et al. Amindoust et al. Li et al.
Environ- mental	Energy usage Pollution reduction Environmental skill Eco-design Environmental awareness	Energy power system Automotive spare parts Watch manufacturer Selection Supplier selection Photo-voltaic module Supplier selection	Journal of Cleaner Production Journal of Manufacturing Systems Information Sciences Expert Systems With Applications Energy	Lin et al. Ashkan et al. Liu et al. Yu et al. Wu et al.

Table 1. Criteria of economic	and environmental aspects
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Table 2. Factors of credit aspect

Perspective	Sub-Criterion	Application	Policy	organization
Credit	Administrative reward and penalties	Regulate business	Enterprise integrity management system	SAC
	Quality commitment performance	to ensure sustainable development	Environmental protection enterprise credit evaluation index system	CAEPI
	Contract Compliance		Sustainability for manufacturing organizations	US-UL
	Enterprise overall management quality credit	-	Index of enterprise credit evaluation	SAC
	Tax-paying credit level		Outline of the plan for the construction of the social credit system (2014–2020)	The State Council

Table 3. Specific interpretation of factors

Criterion/factors	Explanations
	Economic (A1)
Technology capability (κ_1)	Suppliers' ability to make products that are up-to-date and meet customers' needs
Confidence in a durable product (κ_2)	Supplier tolerance with respect to the products offered
Price of product (κ_3)	The lowest market price that the purchaser can afford
Financial capability (κ_4)	The suppliers' maintenance of adequate funds to support enterprise operations
Increase in supply flexibility (κ_5)	Different schemes available to satisfy customers' needs
	Environmental (A2)
Energy usage (κ ₆)	Use of green energy to ensure environmental benefits for sustainable development
Pollution reduction (κ_7)	The reduction of pollutants that are emitted into natural environment
Environmental skill (κ_8)	The ability to ensure that the enterprise is pollution-free
Eco-design (κ ₉)	Products designed to protect the environment throughout the life cycle
Environmental awareness (κ_{10})	Awareness of protecting the environment by taking a series of activities
	Credit (A3)
Administrative reward and punishment (κ_{11})	Abide by the national credit law to fulfill legal obligations
Quality commitment performance (κ_{12})	Equivalent products provided to consumers to win trust
Contract compliance (κ_{13})	Establish product quality management standards to ensure compliance with enterprise's specifications
Enterprise overall management quality credit (κ_{14})	Fulfill commitments to meet employees' psychological and physical needs
Tax-paying credit level (κ_{15})	Pay taxes on time to meet expectations for social responsibility

 κ_9 : Eco-design. Wittstruck and Teuteberg (2012) noted that suppliers may provide products with a green image, that is, products designed to be eco-friendly. When the goal is sustainability, designing products with a consideration of the environment makes sense during the whole product lifecycle (Yu et al., 2019).

 κ_{10} : Environmental awareness. To better demonstrate corporate environmental responsibility, decision-makers would rather to choose sustainable suppliers that performs better in reducing pollution (Wu et al., 2019). More practitioners and researchers have focused on sustainable supply chain management to increase environmental awareness (Boudaghi & Farzipoor Saen, 2018). This indicates that environmental awareness is becoming a major concern of experts.

1.3. Credit

As modernization has proceeded, the Chinese government has increased its attention to constructing a social credit system. National policies and programs include sustainable corporate development goals. The enterprise integrity management system (National Standardization Administration of China [SAC], 2015b) highlights administrative rewards and penalties through enterprise credits. The environmental protection enterprise credit evaluation index system (China Environmental Protection Industry Association [CAEPI], 2018) emphasizes the realization of a commitment to quality credits, to produce commodities that meet needs. Social responsibility is a basic factor measuring the enterprise's credit and clearly reporting whether the enterprise operates in a sustainable way (Underwriters Laboratories [US-UL], 2011). Contract compliance is a good proxy for responsibility. The index of enterprise credit evaluation (SAC, 2015a) also reflects whether an enterprise's overall management quality credit is strongly related with the establishment of social credit. The outline of the plan for constructing the social credit system (2014-2020) (The State Council, 2014) also clearly states that enterprises should pay taxes according to law. The tax-paying credit level affects the subsequent sustainable development of enterprises. Relevant policies are analyzed and five social factors are sorted out, they are summarized as follows:

 κ_{11} : Administrative reward and penalties (SAC, 2015b);

 κ_{12} : Quality commitment performance (CAEPI, 2018);

 κ_{13} : Contract compliance (US-UL, 2011);

 κ_{14} : Enterprise overall management quality credit (SAC, 2015a);

κ₁₅: Tax-paying credit level (State Council, 2014).

2. Preliminaries

Pang et al. (2016) first put forward the probabilistic linguistic term sets (PLTSs), composed of probable linguistic terms as well as equivalent probabilistic values. As an extension of hesitant fuzzy linguistic term sets (HFLTs) (Rodriguez et al., 2011), PLTSs considers different weight of possible linguistic term set (LTS) to generate more reasonable results (Gou & Xu, 2016; Wang et al., 2021; Lei et al., 2020a).

Definition 1 (Pang et al., 2016). Let $S_2 = \{s_0, s_1, ..., s_{\tau}\}$ be a LTS with asymmetric subscripts. And PLTS can be expressed in the form of mathematics as follows:

$$L(p) = \{L^{(k)}(p^{(k)}) \middle| L^{(k)} \in S_2, p^{(k)} \ge 0, k = 1, 2, \dots, \#L(p), \sum_{k=1}^{\#L(p)} p^{(k)} \le 1\},$$
(1)

where the element $L^{(k)}p^{(k)}$ is composed of the *k*-th linguistic term $L^{(k)}$ and its probability $p^{(k)}$ and the term #L(p) denotes the number of elements in L(p). The linguistic terms $L^{(k)}$, k = 1, 2, ..., #L(p) in L(p) are arranged in ascending order.

From Definition 1, $\sum_{k=1}^{\#L(p)} p^{(k)} \le 1$ means that the sum of probabilities in a PLTS is less than 1. This implies that experts only evaluate partial objects. We use the probability aggregation method (Pang et al., 2016) to integrate the experts' opinions, which are expressed as the LTS. Then, we transform the evaluation of LTS into PLTSs collectively. Example 1 shows

Example 1. A hundred consumers are invited to express how they feel about the overall comfortable degree of a sofa. Suppose that sixty-five consumers state that it is high, twenty consumers state that it is very high, ten consumers insist that it is slightly high, and others do not express any opinions. In this case, the obtained information can be summarized as follows: Comfort = {slightly high (0.1), high (0.65), very high (0.2)}. Suppose that LTS can be indicated as: $S = \{S_0 = \text{very low}, S_1 = \text{low}, S_2 = \text{slightly low}, S_3 = \text{fair}, S_4 = \text{slightly high}, S_5 = \text{high}, S_6 = \text{very high}$, then the PLTS can be denoted as $L(p) = \{S_4(0.1), S_5(0.65), S_6(0.2)\}$.

The expressions $L_1(p) = \{L_1^{(k)} p_1^{(k)} | k = 1, 2, ..., \#L_1(p)\}$ and $L_2(p) = \{L_2^{(k)} p_2^{(k)} | k = 1, 2, ..., L_2(p)\}$ are two PLTSs. Having different numbers of linguistic terms in PLTSs places the subsequent calculation in conflict. As such, Pang et al. (2016) proposed the following method to extend the terms to have the same number of elements. If $\#L_1(p) > \#L_2(p)$, then $\#L_1(p) - \#L_2(p)$ linguistic terms are added into $L_2(p)$ making the numbers of elements in the two PLTSs equal. The added linguistic terms have the smallest subscript in, and the probabilities of added linguistic terms are zero (Lin et al., 2018a). This yields the normalized PLTSs (NPLTSs).

Definition 2 (Zhang et al., 2019). Suppose L(p) be a PLTS on the linguistic evaluation scale $S = \{s_{\alpha} \mid \alpha = -\tau, ..., -1, 0, 1, ..., \tau\}$, and $L(p)^N$ be the equivalent NPLTSs. The measurement of L(p) can be calculated by:

$$S^{\zeta}(L(p)) = S^{\zeta}(L(p)^{N}) = ((\gamma^{N(1)}p^{N(1)})^{\zeta} + (\gamma^{N(2)}p^{N(2)})^{\zeta} + \dots + (\gamma^{N(\#L(p)^{N})}p^{N(\#L(p)^{N})})^{\zeta})^{\overline{\zeta}},$$
(2)

where the *l*-th linguistic term's $(L^{N(l)})$ subscript in $L(p)^N$ is $\gamma^{N(l)}$; and ζ $(0 \le \zeta \le 1)$ is a parameter given by the decision maker in a specific case.

Definition 3 (Zhang et al., 2019). For any two PLTSs $L(p)_1$ and $L(p)_2$, comparison laws are defined as:

1. If
$$S^{\zeta}(L(p)_1) > S^{\zeta}(L(p)_2)$$
, then $L(p)_1 \succ L(p)_2$;
2. If $S^{\zeta}(L(p)_1) = S^{\zeta}(L(p)_2)$, then $L(p)_1 \sim L(p)_2$;
3. If $S^{\zeta}(L(p)_1) < S^{\zeta}(L(p)_2)$, then $L(p)_1 \prec L(p)_2$. (3)

this conversion.

3. A novel decision-making framework

To construct the novel decision-making framework, we combine PLTSs and DEMATEL methods and then propose relative importance degree, standard relative importance degree, deviation of importance degree and influence degree for identifying CSFs. To avoid making decisions subjective, we integrate entropy weighting approach and DEMATEL to calculate weights. Considering the psychological changes of experts, we redefine the dominance degree based on standard relative importance degree and comparison laws to combine the TODIM and DEMATEL method in this framework. The decision-making framework is as Figure 1 shows.

3.1. Assessment of importance and influence degree in PLTSs

The existing score function of PLTSs is used to rank and measure, it cannot reflect the interaction between factors. Therefore, according to score function and degree of deviation (Pang et al., 2016), we further propose the relative importance degree, standard relative importance degree, deviation of importance degree and influence degree of PLTSs to combine PLTSs and DEMATEL.

Definition 4. Let $L(p) = \{l^{(k)}(p^{(k)})\} | k = 1, 2, ..., \#L(p)\}$ be a PLTS; $r^{(k)}$ is the *k*-th PLTS's subscript; $p^{(k)}$ stands for the probability of the *k*-th linguistic term (k = 1, 2, ..., #l(p)); #l(p) is the amount of linguistic terms of L(p). Thus, the relative importance degree of L(p) is calculated as:

$$I(L(p)) = \left(\sum_{k=1}^{\#l(p)} r^{(k)} p^{(k)}\right) (\#l(p))^{-1}, k = 1, 2, \dots, \#l(p).$$
(4)

Definition 5. Given a PLTS L(p), the standard relative importance degree of L(p) can be calculated by:

$$SI(L(p)) = \left(\sum_{k=1}^{\#l(p)} (r^{(k)})(p^{(k)})^3\right)^{\frac{1}{2}} (\#l(p))^{-\frac{3}{2}}.$$
(5)

Definition 6. *SI* is the standard relative importance degree of L(p) in the standard relative importance matrix $\left[SI_{ij}\right]_{n \times n}$ (i, j = 1, 2, ..., n). We define the deviation in the importance degree as:

$$\tilde{\rho} = SI^+ - SI^-,\tag{6}$$

where $SI^+ = \underset{i}{Max}(\max_{j} [SI_{ij}])(i, j = 1, 2, ..., n)$ denotes a superior standard relative importance degree, and $SI^- = \underset{i}{Min}(\max_{j} [SI_{ij}])(i, j = 1, 2, ..., n)$ denotes an inferior standard relative importance degree.

Definition 7. $\tilde{\rho}$ is the deviation in the importance degree, based on the standard relative importance matrix $[SI_{ij}]_{n \times n}$ (*i*, *j* = 1,2,...,*n*). The influence degree of *L*(*p*) can be calculated by the following function:

$$\$(L(p)) = \frac{\sqrt{\sum_{k=1}^{\#l(p)} (p^{(k)})^2 (r^{(k)} p^{(k)} - \tilde{\rho})^2}}{(\#l(p))^2}, k = 1, 2, \dots, \#l(p).$$
(7)



Figure 1. The decision-making framework of this paper

3.2. Identifying CSFs

Having different occurrence probabilities of all possible linguistic terms, PLTSs reflect experts' preference rationally (Gao et al., 2019). Thus PLTS DEMATEL method reveals the interaction relationship among different factors (Hu et al., 2021; Xu & Wang, 2017). In line with identification of CSFs, this decision-making framework adopts the DEMATEL method on the basis of PLTSs. And the specific steps are shown as follows:

Step 1. Making initial linguistic evaluation on interaction relationship between factors. Adopt κ_i to represent the factors of SSS introduced in Section 1. Establish a linguistic term scale (Table 4) for SSS factors' pair-wise comparisons for experts, which is consistent with the desired purpose of evaluating the interaction between factors. Different linguistic terms in the linguistic scale { S_0 , S_1 , S_2 , S_3 , S_4 } refers to different degree of direct influence between any two factors, they stand for "no", "very low", "low", "high" and "very high" to assess the influence in turn. Develop a questionnaire and then collect the experts' opinions. Then we generate the initial linguistic evaluation matrix.

Linguistic term	Linguistic variables
S ₀	no
S ₁	very low
S2	low
S ₃	high
S4	very high

Table 4. Linguistic term scale for sustainable supplier selection factors' pair-wise comparisons

Step 2. Calculating the relative importance matrix. Based on the probability aggregation method in Definition 1, convert experts' linguistic assessments into corresponding PLTSs. To force PLTSs to have same number of linguistic terms, PLTSs are transformed into NPLTSs. Based on the NPLTSs, the relative importance matrix is generated using Eq. (4).

Step 3. Obtaining the standard relative importance matrix. Using Eq. (5), generate the standard relative importance matrix.

Step 4. Generating the initial direct matrix. According to standard relative importance matrix, generate an initial direct relation matrix of DEMATEL method, by using the deviation on the importance degree (Eq. (6)) and the influence degree function (Eq. (7)). The initial direct relation matrix shows the influential relationship between factors. The character *Mij* represents the degree that the factor *i*-th affects the factor *j*-th in $n \times n$ non-negative matrix *M*.

Step 5. Normalizing initial direct relation matrix. Calculate the normalized initial direct relation matrix as:

$$U = \frac{M}{\max_{i=1}^{n} \left\{ \sum_{j=1}^{n} m_{ij} \right\}}.$$
(8)

Step 6. Constructing the total relation matrix. Compute the total relation matrix *T* using Eq. (9). *I* is the $n \times n$ unit matrices; and *U* represents the normalized initial direct relation matrix. According to the matrix inversion (Wu & Chang, 2015), the total relation matrix *T* can be denoted as follows:

$$T = U(I - U)^{-1}, (9)$$

where $T = [t_{ij}]_{n \times n}$ (*i*, *j* = 1, 2, ..., *n*).

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Step 7. Identifying CSFs. Calculate the sums of each row *i* and column *j* of *T*:

$$R_i = \sum_{i=1}^n t_{ij}, j = 1, 2, \dots, n.$$
(10)

After completing the calculation above, the sum of *i*-th rows R_i (*i* = 1,2,...,*n*) shows both direct and indirect effects, given by *i*-th factor to the other factors.

$$C_j = \sum_{j=1}^n t_{ji}, i = 1, 2, \dots n.$$
(11)

The sum of the *j*-th columns C_j (j = 1, 2, ..., n) regarding matrix *T* indicates both direct and indirect effects by the *j*-th factor from the other factors.

According to above R_i and C_j , compute the overall prominence P_i and the causal degree E_i in the DEMATEL method using Eq. (12) and Eq. (13).

$$P_i = \left\{ R_i + C_j, \, i = j \right\}. \tag{12}$$

The larger P_i is, the better the overall dominance of the *i*-th factor with respect to its overall relationship with other factors is.

$$E_i = \left\{ R_i - C_j, \, i = j \right\}. \tag{13}$$

As for the causal degree, the *i*-th factor is a net effect of other factors if $E_i < 0$. Factors with a negative E_i value are in the effect group. Otherwise, if $E_i > 0$, then the *i*-th factor is a net cause (Tzeng et al., 2007). CSFs are the factors with positive values of E_i , and they affect other factors. Thus, we use κ'_{λ} ($\lambda = 1, 2, ..., s; 1 \le s \le n$) to represent the identified CSFs by using DEMATEL method.

3.3. Entropy weighting approach with DEMATEL method

Entropy weighting approach is an objective weighting method. It calculates entropy value of CSF, and then determines the weight of the CSF according to the influence of each CSF on the whole system. As a method widely used in various fields, it eliminates the subjectivity of other weight determination methods, such as AHP, ANP, DEMATEL method. For ensuring the authenticity and validity of our decision-making framework, entropy weighting method is adopted based on the determination of CSFs' casual degree, which is obtained by DEMATEL method. The specific steps for calculating weights can be summarized as follows:

Step 1. Normalize initial data. The casual degree value of CSFs in total influence matrix, obtained from DEMATEL method, is taken as the initial value. And $E_i > 0$, so we need to calculate the proportion of *j*-th CSF in CSFs' system for revealing the variation degree of this CSF.

$$V_{ij} = \frac{E_i}{\sum_{i=1}^{n} E_i}.$$
(14)

Step 2. Calculate entropy value of each CSF based on normalized initial data from DE-MATEL method.

$$e_j = -\Lambda \sum_{i=1}^{6} V_{ij} \ln(V_{ij}),$$
 (15)

where $\Lambda = \frac{1}{\ln n}$, and e_j is [0,1].

Step 3. Compute the weight of λ -th CSF.

$$W_{\lambda} = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j} (\lambda = 1, 2, \dots, n \le s \le n).$$
(16)

3.4. SSS with TODIM method based on PLTSs

To fully consider the psychological state of experts, we adopt TODIM method based on prospect theory to make SSS in decision-making framework. During the process, we redefine the dominance degree in TODIM based on standard relative importance degree (Definition 5) as well as comparison laws (Zhang et al., 2019).

Definition 8. According to the classical TODIM method, we propose a new rule to measure the dominance degree of the *x*-th supplier π_x to the *y*-th supplier π_y . Considering the identified CSFs κ'_{λ} ($\lambda = 1, 2, ..., s; 1 \le s \le n$), it is defined by:

$$\varphi_{\lambda}'(o_{x},o_{y}) = \begin{cases} \sqrt{\frac{w_{\lambda/\lambda^{*}}\Gamma(SI(L(p)_{xj}),SI(L(p)_{yj}))}{\sum_{\lambda=1}^{s}w_{\lambda/\lambda^{*}}}}, & \text{if } S^{\zeta}(L(p)_{xj}) - S^{\zeta}(L(p)_{yj}) > 0\\ 0, & \text{if } S^{\zeta}(L(p)_{xj}) - S^{\zeta}(L(p)_{yj}) = 0\\ -\frac{1}{\mu}\sqrt{\frac{\sum_{\lambda=1}^{s}w_{\lambda/\lambda^{*}}\Gamma(SI(L(p)_{xj}),SI(L(p)_{yj})))}{w_{\lambda/\lambda^{*}}}}, & \text{if } S^{\zeta}(L(p)_{xj}) - S^{\zeta}(L(p)_{yj}) < 0 \end{cases}$$
(17)

The expression $w_{\lambda/\lambda^*} = \frac{w_\lambda}{\max w_\lambda}$ ($\lambda = 1, 2, ..., s; 1 \le s \le n$) represents the relative weight of κ'_λ . Parameter $\mu(\mu > 0)$ is the attenuation factor of the loss, which is inversely proportional to the degree of loss aversion. According to Definition 5, $\Gamma(SI(L(p)_{xj}), SI(L(p)_{yj})))$ is the difference in the standard relative importance between two PLTSs. It equals $\Gamma(SI(L(p)_{xj}), SI(L(p)_{yj})) = |SI(L(p)_{xj}) - SI(L(p)_{yj})|$.

According to the new definition above, the following steps are applied into SSS based on TODIM method:

Step 1. Collect expert evaluations and convert them into an initial matrix of probabilistic linguistic terms $D = (L(p)_{ij})_{m \times n}$, based on the probabilistic linguistic evaluation scale (Table 5). Experts are invited to complete questionnaires for reporting their judgments about potential suppliers.

Linguistic evaluation scale	Linguistic variables
S_3	pretty bad
S ₋₂	bad
S_1	a little bad
S ₀	middle
S ₁	a little good
S2	good
S ₃	pretty good

Table 5. Linguistic term scale for sustainable supplier selection

Step 2. According to Xu (2012), normalize the initial probabilistic linguistic terms matrix $D = (L(p)_{ii})_{m \times n}$ and transform the cost attributes into benefit attributes.

Step 3. Determine the relative weights of CSFs. Apply Eq. (16) to calculate the weights of the CSFs. Then, factor with the largest weight can be selected as the reference factor (marked as max w_{λ}) and compute the relative weight of κ'_{λ} :

$$w_{\lambda/\lambda^*} = \frac{w_{\lambda}}{\max w_{\lambda}} (\lambda = 1, 2, \dots, s; 1 \le s \le n).$$

Step 4. Determine the dominance matrix $\phi'_{\lambda}(\pi_x, \pi_y)$, and compare one supplier against another supplier under each CSF by Eq. (17).

Step 5. Calculate the overall dominance degree $\varphi'(\pi_x, \pi_y)$ for the supplier π_x to the supplier π_y by using Eq. (18). The overall dominance degree is calculated as:

$$\varphi'(\pi_x, \pi_y) = \sum_{\lambda=1}^{s} \varphi'_{\lambda}(\pi_x, \pi_y).$$
(18)

Step 6. Generate the overall values $\Phi'(\pi_x)$ (x = 1, 2, ..., n) in the *i*-th row and rank the whole values to get the most sustainable supplier. The overall values of the supplier π_x are:

$$\Phi'(\pi_{x}) = \frac{\sum_{y=1}^{m} \varphi'(\pi_{x}, \pi_{y}) - \min_{i} \left\{ \sum_{y=1}^{m} \varphi'(\pi_{x}, \pi_{y}) \right\}}{\max_{i} \left\{ \sum_{y=1}^{m} \varphi'(\pi_{x}, \pi_{y}) \right\} - \min_{i} \left\{ \sum_{y=1}^{m} \varphi'(\pi_{x}, \pi_{y}) \right\}},$$
(19)

where $0 \le \Phi'(\pi_x) \le 1$.

4. Case study

For verifying the usefulness of the proposed decision-making framework, a case study of NEVs is provided in this section.

4.1. Background information about the case

Fuel consumption in the auto industry is a concern, because it accounts for nearly 40% of Chinese total fuel consumption (Zhang & Bai, 2017). Chinese import volumes of net crude oil exceeded 500 million tons for the first time in 2019 (General Administration of Customs of the People's Republic of China, 2019). At the same time, high levels of vehicle fuel consumption can lead to frequent smoggy weather; studies also show that exhaust fumes of motor vehicles are a main source of particulate matter in Beijing, Shanghai, and other large cities in China (Wang et al., 2014). NEVs effectively alleviate air pollution and energy shortages (The State Council, 2012; Wei et al., 2021b). Hence, the Chinese government has introduced several policies to promote the sustainable development of NEVs (Liu et al., 2018). The traditional automobile enterprises Mercedes-Benz, Volkswagen, and Honda have accelerated the layout of NEVs worldwide. Given these circumstances, selecting a high-performing sustainable supplier will enhance the sustainable development level of the automotive industry (Chinese State Council, 2014). As such, we choose this setting as our case study.

The case study focuses on providing the Chinese NEV company with a method for SSS for further development. Three stages are applied to construct a novel decision-making framework for selecting sustainable suppliers. First, DEMATEL method is combined with PLTSs to identify CSFs. Second, we combine entropy weighting approach and DEMATEL to determine CSFs' weights. Third, we adopt the TODIM method to choose the best sustainable NEVs supplier in the framework. In order to do a quantitative study, we invite 5 professional experts in the fields of NEV management. And the experts' background information is presented in Table 6.

Experts	Age	Service tenure	Gender	Educational background	Occupational background	Job title
Ex1	46	>15	Male	Master	Governmental	Research director
Ex2	50	>23	Female	Bachelor	Industrial	Financial controller
Ex3	39	>21	Male	Master	Industrial	Chief technology officer
Ex4	45	>18	Male	Master	Industrial	Legal specialist
Ex5	42	>13	Female	Doctoral	Academic	Associate professor

Table 6. Background information of experts

4.2. Calculation process of DEMATEL method based on PLTSs

This part completes a numerical example for identifying CSFs and determining their weights in the decision-making framework, by applying DEMATEL method under PLTSs to the case study in NEV Company. The calculation process is listed as follows.

Step 1. Develop initial linguistic evaluation matrix to determine interaction between factors. We use questionnaires (in Supplementary information) to collect 5 experts' evaluation on interactive influence between factors. Using the established linguistic term scale for sustainable supplier selection factors' pair-wise comparisons (Table 4), we generate initial evaluation matrix of PLTSs (Supplementary information Table S3).

Step 2. Construct the relative importance matrix (Table 7). The initial linguistic evaluation matrix is transformed into a PLTS form (Supplementary information Table S4). Then we use a normalization calculation (Pang et al., 2016) to produce NPLTSs (Supplementary information Table S5). Using Eq. (4), we generate a relative importance matrix based on the NPLTSs.

No.	k_1	<i>k</i> ₂	<i>k</i> ₃	k_4	<i>k</i> ₅	k_6	<i>k</i> ₇	<i>k</i> ₈	k_9	<i>k</i> ₁₀	<i>k</i> ₁₁	<i>k</i> ₁₂	<i>k</i> ₁₃	<i>k</i> ₁₄	<i>k</i> ₁₅
k_1	0.00	0.48	0.35	0.64	0.32	0.56	0.44	0.60	0.32	0.12	0.52	0.40	0.24	0.12	0.40
<i>k</i> ₂	0.24	0.00	0.36	0.25	0.32	0.20	0.44	0.20	0.32	0.32	0.24	0.20	0.40	0.24	0.56
<i>k</i> ₃	0.16	0.40	0.00	0.36	0.52	0.36	0.25	0.16	0.52	0.24	0.16	0.24	0.24	0.12	0.32
k_4	0.60	0.56	0.32	0.00	0.48	0.64	0.40	0.44	0.48	0.64	0.60	0.36	0.28	0.32	0.64
k_5	0.24	0.50	0.52	0.52	0.00	0.36	0.36	0.24	0.16	0.24	0.24	0.24	0.20	0.16	0.16
k_6	0.48	0.12	0.24	0.24	0.16	0.00	0.44	0.64	0.16	0.60	0.48	0.20	0.36	0.20	0.44
<i>k</i> ₇	0.60	0.20	0.16	0.64	0.36	0.40	0.00	0.56	0.36	0.48	0.60	0.16	0.20	0.12	0.68
<i>k</i> ₈	0.20	0.56	0.56	0.20	0.35	0.28	0.56	0.00	0.35	0.48	0.20	0.52	0.24	0.56	0.15
k_9	0.44	0.28	0.12	0.56	0.28	0.36	0.24	0.52	0.00	0.44	0.44	0.16	0.44	0.56	0.40
<i>k</i> ₁₀	0.20	0.40	0.20	0.52	0.44	0.24	0.32	0.20	0.44	0.00	0.20	0.52	0.16	0.24	0.12
<i>k</i> ₁₁	0.24	0.20	0.20	0.12	0.16	0.52	0.52	0.60	0.16	0.44	0.00	0.10	0.16	0.56	0.32
<i>k</i> ₁₂	0.44	0.44	0.40	0.44	0.64	0.36	0.24	0.20	0.64	0.20	0.44	0.00	0.30	0.52	0.24
<i>k</i> ₁₃	0.44	0.08	0.24	0.36	0.20	0.16	0.20	0.36	0.20	0.24	0.44	0.08	0.00	0.08	0.20
<i>k</i> ₁₄	0.24	0.44	0.40	0.24	0.32	0.56	0.40	0.20	0.32	0.16	0.24	0.24	0.32	0.00	0.40
<i>k</i> ₁₅	0.24	0.16	0.24	0.48	0.28	0.36	0.16	0.20	0.28	0.12	0.24	0.20	0.20	0.32	0.00

Table 7. Matrix of the relative importance relationships

Step 3. Calculate the standard relative importance matrix. To more accurately calculate the importance degree between factors, we adopt Eq. (5) to compute the standard relative importance matrix (Table 8).

Step 4. Compute the initial direct relationship matrix. The initial direct relationship between factors depicts their degree of interaction with each other. Table 9 provides the initial direct relationship matrix, generated using Eq. (6) and Eq. (7).

Step 5. Normalize the initial direct relationship matrix based on Eq. (8).

Step 6. Construct total relationship matrix. Generate total relationship matrix (Table 10) using Eq. (9).

No.	k_1	k_2	<i>k</i> ₃	k_4	k_5	k_6	<i>k</i> ₇	k ₈
<i>k</i> ₁	0.000	0.139	0.118	0.160	0.113	0.150	0.133	0.155
<i>k</i> ₂	0.098	0.000	0.120	0.100	0.113	0.089	0.133	0.089
<i>k</i> ₃	0.080	0.126	0.000	0.120	0.144	0.120	0.100	0.080
k_4	0.155	0.150	0.113	0.000	0.139	0.160	0.126	0.133
<i>k</i> ₅	0.098	0.141	0.144	0.144	0.000	0.120	0.120	0.098
k ₆	0.139	0.069	0.098	0.098	0.080	0.000	0.133	0.160
<i>k</i> ₇	0.155	0.089	0.080	0.160	0.120	0.126	0.000	0.150

Table 8. Matrix of the standard relative importance considering the factors

End	of	Table	8
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No.	k_1	k_2		<i>k</i> ₃	k	4	k_5		k ₆	k ₇	k ₈
k ₈	0.089	0.150	0.	.150	0.0)89	0.11	8	0.106	0.150	0.000
<i>k</i> ₉	0.133	0.106	0.	.069	0.1	50	0.10	6	0.120	0.098	0.144
k ₁₀	0.089	0.126	0.	.089	0.1	44	0.13	3	0.098	0.113	0.089
k ₁₁	0.098	0.089	0.	.089	0.0)69	0.08	0	0.144	0.144	0.155
k ₁₂	0.133	0.133	0.	.126	0.1	33	0.16	0	0.120	0.098	0.089
k ₁₃	0.133	0.057	0.	.098	0.1	20	0.08	9	0.080	0.089	0.120
k ₁₄	0.098	0.133	0.	.126	0.0)98	0.11	3	0.150	0.126	0.089
k ₁₅	0.098	0.080	0.	.098	0.1	39	0.10	6	0.120	0.080	0.089
No.	k_9	k ₁₀		k_1	1	ŀ	² 12		<i>k</i> ₁₃	k_{14}	k_{15}
<i>k</i> ₁	0.113	0.069)	0.14	14	0.	126	(0.098	0.069	0.126
<i>k</i> ₂	0.113	0.113	3	0.09	98	0.	089	(0.126	0.098	0.150
<i>k</i> ₃	0.144	0.098	3	0.08	30	0.	098	(0.098	0.069	0.113
k_4	0.139	0.160)	0.1	55	0.	120	(0.106	0.113	0.160
k_5	0.080	0.098	3	0.0	98	0.	098	(0.089	0.080	0.080
<i>k</i> ₆	0.080	0.155	5	0.13	39	0.	089	(0.120	0.089	0.133
k ₇	0.120	0.139)	0.15	55	0.	080	(0.089	0.069	0.165
k ₈	0.118	0.139)	0.08	39	0.	144	(0.098	0.150	0.077
<i>k</i> 9	0.000	0.133	3	0.13	33	0.	080		0.133	0.150	0.126
k ₁₀	0.133	0.000)	0.08	39	0.	144	(0.080	0.098	0.069
k ₁₁	0.080	0.133	3	0.0	00	0.	063	(0.080	0.150	0.113
k ₁₂	0.160	0.089)	0.13	33	0.	000	(0.110	0.144	0.098
k ₁₃	0.089	0.098	3	0.13	33	0.	057	(0.000	0.057	0.089
k ₁₄	0.113	0.080)	0.09	98	0.	098	(0.113	0.000	0.126
k ₁₅	0.106	0.069)	0.09	98	0.	089	(0.089	0.113	0.000

Table 9. The initial direct relationship matrix

No.	k_1	<i>k</i> ₂	<i>k</i> ₃	k_4	k_5	k_6	k ₇	k_8
<i>k</i> ₁	0.0330	0.4470	0.3170	0.6070	0.2870	0.5270	0.4070	0.5670
<i>k</i> ₂	0.2070	0.0330	0.3270	0.2170	0.2870	0.1670	0.4070	0.1670
<i>k</i> ₃	0.1270	0.3670	0.0330	0.3270	0.4870	0.3270	0.2170	0.1270
k_4	0.5670	0.5270	0.2870	0.0330	0.4470	0.6070	0.3670	0.4070
<i>k</i> ₅	0.2070	0.4670	0.4870	0.4870	0.0330	0.3270	0.3270	0.2070
<i>k</i> ₆	0.4470	0.0870	0.2070	0.2070	0.1270	0.0330	0.4070	0.6070
<i>k</i> ₇	0.5670	0.1670	0.1270	0.6070	0.3270	0.3670	0.0330	0.5270
<i>k</i> ₈	0.1670	0.5270	0.5270	0.1670	0.3170	0.2470	0.5270	0.0330
<i>k</i> ₉	0.4070	0.2470	0.0870	0.5270	0.2470	0.3270	0.2070	0.4870
k ₁₀	0.1670	0.3670	0.1670	0.4870	0.4070	0.2070	0.2870	0.1670
<i>k</i> ₁₁	0.2070	0.1670	0.1670	0.0870	0.1270	0.4870	0.4870	0.5670
k ₁₂	0.4070	0.4070	0.3670	0.4070	0.6070	0.3270	0.2070	0.1670
k ₁₃	0.4070	0.0470	0.2070	0.3270	0.1670	0.1270	0.1670	0.3270
k ₁₄	0.2070	0.4070	0.3670	0.2070	0.2870	0.5270	0.3670	0.1670
k ₁₅	0.2070	0.1270	0.2070	0.4470	0.2470	0.3270	0.1270	0.1670

End of Table 9

No.	k_9	k_{10}	k_{11}	k ₁₂	k ₁₃	k_{14}	k_{15}
k_1	0.2870	0.0870	0.4870	0.3670	0.2070	0.0870	0.3670
k ₂	0.2870	0.2870	0.2070	0.1670	0.3670	0.2070	0.5270
k ₃	0.4870	0.2070	0.1270	0.2070	0.2070	0.0870	0.2870
k_4	0.4470	0.6070	0.5670	0.3270	0.2470	0.2870	0.6070
k_5	0.1270	0.2070	0.2070	0.2070	0.1670	0.1270	0.1270
<i>k</i> ₆	0.1270	0.5670	0.4470	0.1670	0.3270	0.1670	0.4070
k ₇	0.3270	0.4470	0.5670	0.1270	0.1670	0.0870	0.6470
k ₈	0.3170	0.4470	0.1670	0.4870	0.2070	0.5270	0.1170
k_9	0.0330	0.4070	0.4070	0.1270	0.4070	0.5270	0.3670
k ₁₀	0.4070	0.0330	0.1670	0.4870	0.1270	0.2070	0.0870
k ₁₁	0.1270	0.4070	0.0330	0.0670	0.1270	0.5270	0.2870
k ₁₂	0.6070	0.1670	0.4070	0.0330	0.2670	0.4870	0.2070
k ₁₃	0.1670	0.2070	0.4070	0.0470	0.0330	0.0470	0.1670
<i>k</i> ₁₄	0.2870	0.1270	0.2070	0.2070	0.2870	0.0330	0.3670
<i>k</i> ₁₅	0.2470	0.0870	0.2070	0.1670	0.1670	0.2870	0.0330

Table 10. Total relationship matrix

No.	k_1	k_2	<i>k</i> ₃	k_4	k_5	k_6	k ₇	k ₈
k_1	0.1268	0.1882	0.1557	0.2272	0.1629	0.2158	0.1905	0.2191
k ₂	0.1194	0.0911	0.1259	0.1380	0.1306	0.1246	0.1511	0.1208
<i>k</i> ₃	0.1054	0.1401	0.0796	0.1497	0.1569	0.1440	0.1210	0.1122
k_4	0.2262	0.2221	0.1706	0.1731	0.2083	0.2528	0.2083	0.2202
<i>k</i> ₅	0.1205	0.1598	0.1516	0.1745	0.0945	0.1493	0.1430	0.1276
k ₆	0.1655	0.1153	0.1207	0.1490	0.1193	0.1182	0.1687	0.2019
<i>k</i> ₇	0.2037	0.1476	0.1260	0.2299	0.1668	0.1938	0.1335	0.2136
<i>k</i> ₈	0.1351	0.1911	0.1774	0.1554	0.1612	0.1611	0.1940	0.1212
<i>k</i> ₉	0.1725	0.1514	0.1144	0.2066	0.1471	0.1781	0.1521	0.1964
k ₁₀	0.1195	0.1501	0.1078	0.1806	0.1549	0.1362	0.1396	0.1251
<i>k</i> ₁₁	0.1203	0.1159	0.1063	0.1172	0.1079	0.1745	0.1704	0.1840
k ₁₂	0.1780	0.1807	0.1603	0.1979	0.2062	0.1847	0.1561	0.1553
k ₁₃	0.1292	0.0783	0.0926	0.1289	0.0931	0.0995	0.1001	0.1277
k ₁₄	0.1253	0.1515	0.1369	0.1397	0.1345	0.1828	0.1525	0.1284
k ₁₅	0.1062	0.0945	0.0971	0.1513	0.1102	0.1348	0.0977	0.1073

No.	<i>k</i> ₉	k ₁₀	k ₁₁	k ₁₂	k ₁₃	k ₁₄	k ₁₅
k_1	0.1599	0.1413	0.2021	0.1455	0.1237	0.1199	0.1868
k2	0.1282	0.1309	0.1246	0.0902	0.1216	0.1049	0.1730
<i>k</i> ₃	0.1540	0.1188	0.1100	0.0938	0.0976	0.0860	0.1348
k_4	0.2044	0.2362	0.2359	0.1583	0.1469	0.1675	0.2434
<i>k</i> ₅	0.1071	0.1236	0.1256	0.0979	0.0933	0.0928	0.1177
k ₆	0.1171	0.1869	0.1727	0.1047	0.1231	0.1128	0.1655
k ₇	0.1637	0.1910	0.2124	0.1129	0.1149	0.1195	0.2240
k ₈	0.1582	0.1772	0.1409	0.1556	0.1169	0.1717	0.1377
<i>k</i> ₉	0.1117	0.1756	0.1799	0.1058	0.1461	0.1757	0.1746
k ₁₀	0.1520	0.0992	0.1247	0.1418	0.0909	0.1115	0.1137
k ₁₁	0.1059	0.1541	0.0987	0.0807	0.0876	0.1560	0.1397
k ₁₂	0.2024	0.1446	0.1857	0.0909	0.1318	0.1736	0.1586
k ₁₃	0.0914	0.1027	0.1348	0.0609	0.0556	0.0675	0.0985
k ₁₄	0.1320	0.1148	0.1307	0.0989	0.1154	0.0820	0.1568
k ₁₅	0.1082	0.0900	0.1108	0.0804	0.0822	0.1065	0.0849

End of Table 10

Step 7. Identify CSFs. Using Eq. (10) and Eq. (11), we calculate R_i and C_j , leading to the overall dominance P_i and the causal degree E_i (Table 11).

No.	R _i	C_j	P_i	Ei
k_1	2.57	2.15	4.72	0.41
k_2	1.87	2.18	4.05	-0.30
k ₃	1.80	1.92	3.73	-0.12
k_4	3.07	2.52	5.59	0.56
k ₅	1.88	2.15	4.03	-0.28
k ₆	2.14	2.45	4.59	-0.31
k ₇	2.55	2.28	4.83	0.27
k	2.35	2.36	4.72	-0.01
k_9	2.39	2.10	4.48	0.29
k ₁₀	1.95	2.19	4.13	-0.24
k ₁₁	1.92	2.29	4.21	-0.37
k ₁₂	2.51	1.62	4.13	0.89
k ₁₃	1.46	1.65	3.11	-0.19
k ₁₄	1.98	1.85	3.83	0.13
k ₁₅	1.56	2.31	3.87	-0.75

Table 11. Effect and cause relationships between factors



Figure 2. The cause-effect graph of supplier selection factors

Figure 2 provides the resulting cause-effect diagram, according to the values of P_i and E_i calculated by using Eq. (12) and (13) in Table 11. Figure 2 shows that factors are segmented into two different groups based on the values of causal degree E_i . For $E_i < 0$ (i = 2,3,5,6,8,10,11,13,15), κ_2 , κ_3 , κ_6 , κ_8 , κ_{10} , κ_{11} , κ_{13} and κ_{15} form the net effect group. For $E_i > 0$ (i = 1,4,7,9,12,14), κ_1 , κ_4 , κ_7 , κ_9 , κ_{12} and κ_{14} form the net cause group. This indicates they have overall effects on the entire factor system. Therefore, we identify the factors κ'_1 , κ'_4 , κ'_7 , κ'_9 , κ'_{12} , κ'_{14} as CSFs.

4.3. The decision-making process using the TODIM method under PLTSs

After completing calculations using the PLTSs and DEMATEL method, the CSFs κ'_1 , κ'_4 , κ'_7 , κ'_9 , κ'_{12} and κ'_{14} are identified as the CSFs for selecting the most suitable sustainable NEV suppliers. Five alternatives are identified to serve as sustainable NEV suppliers: π_1 , π_2 , π_3 , π_4 and π_5 .

Step 1. We use questionnaires (in Supplementary information) to collect 5 experts' evaluation on potential suppliers' performance. Using the established linguistic term scale for sustainable supplier selection (Table 5), we generate the initial probabilistic linguistic evaluation matrix (Table 12).

Step 2. Calculate NPLTSs and transform cost attributes into benefit attributes. By transforming the initial probabilistic linguistic evaluation matrix into NPLTSs, κ'_7 and κ'_9 are identified as cost attributes. According to negation operation (Xu, 2012), we transform them into benefit attributes. Table 13 displays the results.

Step 3. Compute relative weights of CSFs. On the basis of entropy weighting approach with DEMATEL method, the weight vector of CSFs in this paper is $w_{\lambda} = (0.164, 0.160, 0.170, 0.169, 0.156, 0.180)^{\text{T}}$. We select the largest weight as the referential weight max $w_{\lambda} = w_6$.

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The relative weight w_{λ/λ^*} is further calculated as $w_{\lambda/\lambda^*} = \frac{w_\lambda}{\max w_\lambda}$ ($\lambda = 1, 2, ..., s; 1 \le s \le n$). This leads to: $w_{1/\lambda^*} = 0.915$, $w_{2/\lambda^*} = 0.892$, $w_{3/\lambda^*} = 0.948$, $w_{4/\lambda^*} = 0.943$, $w_{5/\lambda^*} = 0.870$, and = 1.000.

	κ' ₁	κ'4	κ′ ₇
π_1	$\{S_1(0.2), S_2(0.6), S_3(0.2)\}$	$\{S_{-1}(0.2), S_1(0.2), S_2(0.6)\}$	{ $S_{-3}(0.4), S_{-1}(0.2), S_{2}(0.4)$ }
π2	$\{S_{-3}(1)\}$	$\{S_{-2}(0.4), S_0(0.4)\}$	$\{S_{-2}(0.5), S_{-1}(0.5)\}$
π3	$\{S_2(0.2), S_3(0.8)\}$	$\{S_0(0.6), S_2(0.4)\}$	$\{S_{-2}(0.2), S_0(0.6)\}$
π_4	$\{S_1(0.4), S_3(0.6)\}$	$\{S_0(0.4), S_2(0.4), S_3(0.2)\}$	$\{S_{-1}(0.8), S_0(0.2)\}$
π ₅	$\{S_1(0.4), S_2(0.6)\}$	{ $S_{-1}(0.4), S_2(0.4), S_3(0.2)$ }	{ $S_{-2}(0.6), S_{-1}(0.2), S_{3}(0.2)$ }
	к′ ₉	κ' ₁₂	κ'_{14}
π_1	$\{S_{-3}(0.4), S_{-2}(0.4)\}$	$\{S_{-2}(0.5), S_0(0.5)\}$	$\{S_1(0.2), S_2(0.6)\}$
π2	$\{S_0(0.4), S_2(0.2), S_3(0.4)\}$	{ $S_{-2}(0.2), S_{-1}(0.6), S_{0}(0.2)$ }	$\{S_{-2}(0.8), S_0(0.2)\}$
π3	{ $S_{-3}(0.2), S_{-2}(0.4), S_{1}(0.2)$ }	$\{S_0(0.6), S_2(0.2)\}$	{ $S_{-3}(0.2), S_{-2}(0.6), S_{0}(0.2)$ }
π_4	$\{S_{-2}(0.4), S_{-1}(0.6)\}$	$\{S_1(0.8), S_2(0.2)\}$	$\{S_0(0.2), S_2(0.6), S_3(0.2)\}$
π_5	{ $S_{-2}(0.2), S_0(0.2), S_3(0.6)$ }	$\{S_1(0.6), S_2(0.2), S_3(0.2)\}$	{ $S_{-1}(0.6), S_0(0.2), S_2(0.2)$ }

Table 12. Initial probabilistic linguistic evaluation matrix

Table 13. Evaluation matrix of NPLTSs

	κ'1	κ'4	κ′ ₇
π1	$\{S_1(0.2), S_2(0.6), S_3(0.2)\}$	$\{S_{-1}(0.2), S_1(0.2), S_2(0.6)\}$	$\{S_{-2}(0.4), S_1(0.2), S_3(0.4)\}$
π2	$\{S_{-3}(0), S_{-3}(0), S_{-3}(1)\}$	$\{S_{-2}(0), S_{-2}(0.4), S_0(0.4)\}$	$\{S_1(0.5), S_2(0), S_2(0.5)\}$
π3	$\{S_2(0), S_2(0.2), S_3(0.8)\}$	$\{S_0(0), S_0(0.2), S_2(0.8)\}$	$\{S_0(0.6), S_2(0), S_2(0.2)\}$
π_4	$\{S_1(0), S_1(0.4), S_3(0.6)\}$	$\{S_0(0.4), S_2(0.4), S_3(0.2)\}$	$\{S_0(0.2), S_1(0), S_1(0.8)\}$
π ₅	$\{S_1(0), S_1(0.4), S_2(0.6)\}$	$\{S_{-1}(0.4), S_2(0.4), S_3(0.2)\}$	$\{S_{-3}(0.2), S_1(0.2), S_2(0.6)\}$
	к′ ₉	κ′ ₁₂	κ′ ₁₄
π_1	$\{S_2(0.4), S_3(0), S_3(0.4)\}$	$\{S_{-2}(0), S_{-2}(0.5), S_{1}(0.5)\}$	$\{S_1(0), S_1(0.2), S_2(0.6)\}$
π2	$\{S_0(0.4), S_2(0.2), S_3(0.4)\}$	{ $S_{-2}(0.2), S_{-1}(0.6), S_{2}(0.2)$ }	$\{S_{-2}(0), S_{-2}(0.8), S_{1}(0.2)\}$
π3	$\{S_{-1}(0.2), S_2(0.4), S_3(0.2)\}$	$\{S_0(0.2), S_1(0.6), S_2(0.2)\}$	{ $S_{-3}(0.2), S_{-2}(0.6), S_{0}(0.2)$ }
π_4	$\{S_1(0.6), S_2(0), S_2(0.4),\}$	$\{S_1(0), S_1(0.8), S_2(0.2)\}$	$\{S_1(0.2), S_2(0.6), S_3(0.2)\}$
π ₅	$\{S_{-2}(0.2), S_0(0.2), S_3(0.6)\}$	$\{S_1(0.6), S_2(0.2), S_3(0.2)\}$	$\{S_{-1}(0.6), S_0(0.2), S_2(0.2)\}$

Step 4. Calculate the dominance matrix $\varphi'_{\lambda}(\pi_x, \pi_y)$. Using Definitions 2 and 3, we assign $\zeta = 0.1$ to obtain the comparative results of any two sustainable suppliers, in the case of a loss in generality.

For example, when considering κ'_1 (Technology capability), the evaluation value of π_1 is $\{S_1(0.2), S_2(0.6), S_3(0.2)\}$, while the value of π_2 is $\{S_{-3}(0), S_{-3}(0), S_{-3}(1)\}$. Calculating $S^{\zeta}(L(p))$ (Eq. (5)) resulted in $S^{0.1}(L(p)_{11}) = 31797.8629 > S^{0.1}(L(p)_{21}) = 3.0000$. This means that supplier π_1 is rated as better than supplier π_2 when take the consideration of financial capacity, denoted as $(\pi_1 > \pi_2)^{\kappa'_{12}}$. Similarly, Table 14 shows the pairwise comparison of suppliers considering different CSFs.

For the sake of generality, let $\mu = 1$. We adopt Eq. (17) to determine the dominance degree of the sustainable supplier π_x over the other supplier π_y considering each CSF. And the results are shown in Tables 15–20.

	π_1 / π_2	π_1 / π_3	π_1 / π_4	π_1 / π_5	π_2 / π_3
κ'1	$(\pi_1 > \pi_2)^{k'1}$	$(\pi_1 > \pi_3)^{k'1}$	$(\pi_1 > \pi_4)^{k'1}$	$(\pi_1 > \pi_5)^{k'1}$	$(\pi_2 < \pi_3)^{k'1}$
κ'4	$(\pi_1 > \pi_2)^{k'4}$	$(\pi_1 > \pi_3)^{k'4}$	$(\pi_1 > \pi_4)^{k'4}$	$(\pi_1 < \pi_5)^{k'4}$	$(\pi_2 < \pi_3)^{k'4}$
κ'7	$(\pi_1 > \pi_2)^{k'7}$	$(\pi_1 > \pi_3)^{k'7}$	$(\pi_1 > \pi_4)^{k'7}$	$(\pi_1 > \pi_5)^{k'7}$	$(\pi_2 > \pi_3)^{k'7}$
κ'9	$(\pi_1 > \pi_2)^{k'9}$	$(\pi_1 < \pi_3)^{k'9}$	$(\pi_1 > \pi_4)^{k'9}$	$(\pi_1 > \pi_5)^{k'9}$	$(\pi_2 < \pi_3)^{k'9}$
κ' ₁₂	$(\pi_1 < \pi_2)^{k'12}$	$(\pi_1 < \pi_3)^{k'12}$	$(\pi_1 < \pi_4)^{k'12}$	$(\pi_1 > \pi_5)^{k'12}$	$(\pi_2 < \pi_3)^{k'12}$
κ'_{14}	$(\pi_1 < \pi_2)^{k'14}$	$(\pi_1>\pi_3)^{k'14}$	$(\pi_1>\pi_4)^{k'14}$	$(\pi_1 < \pi_5)^{k'14}$	$(\pi_2>\pi_3)^{k'14}$
	π_2 / π_4	π_2 / π_5	π_3 / π_4	π_3 / π_5	π_4 / π_5
κ' ₁	$(\pi_2 < \pi_4)^{k'1}$	$(\pi_2 < \pi_5)^{k'1}$	$(\pi_3>\pi_4)^{k'1}$	$(\pi_3>\pi_5)^{k'1}$	$(\pi_4>\pi_5)^{k'1}$
κ'4	$(\pi_2 < \pi_4)^{k'4}$	$(\pi_2 < \pi_5)^{k'4}$	$(\pi_3 < \pi_4)^{k'4}$	$(\pi_3 < \pi_5)^{k'4}$	$(\pi_4 < \pi_5)^{k'4}$
κ' ₇	$(\pi_2 > \pi_4)^{k'7}$	$(\pi_2 < \pi_5)^{k'7}$	$(\pi_3 < \pi_4)^{k'7}$	$(\pi_3 < \pi_5)^{k'7}$	$(\pi_4 < \pi_5)^{k'7}$
κ'9	$(\pi_2 > \pi_4)^{k'9}$	$(\pi_2 < \pi_5)^{k'9}$	$(\pi_3 > \pi_4)^{k'9}$	$(\pi_3 > \pi_5)^{k'9}$	$(\pi_4 < \pi_5)^{k'9}$
κ' ₁₂	$(\pi_2 < \pi_4)^{k'12}$	$(\pi_2 > \pi_5)^{k'12}$	$(\pi_3 < \pi_4)^{k'12}$	$(\pi_3 > \pi_5)^{k'12}$	$(\pi_4 > \pi_5)^{k'12}$
κ'_{14}	$(\pi_2 > \pi_4)^{k'14}$	$(\pi_2 > \pi_5)^{k'14}$	$(\pi_3 < \pi_4)^{k'14}$	$(\pi_3 < \pi_5)^{k'14}$	$(\pi_4 < \pi_5)^{k'14}$

Table 14. Pairwise comparison of sustainable suppliers' benefit and loss

Table 15. The dominance degree of supplier π_x over supplier π_y concerning the CSF κ'_1

κ'1	π1	π2	π3	π_4	π_5
π1	0.0000	0.1002	0.0905	0.0467	0.0687
π2	-0.6102	0.0000	-0.2623	-0.5398	-0.7397
π3	-0.5509	0.0431	0.0000	0.0775	0.1136
π4	-0.2843	0.0887	-0.4719	0.0000	0.0831
π ₅	-0.4182	0.1215	-0.6916	-0.5057	0.0000

Table 16. The dominance degree of supplier π_x over supplier π_v concerning the CSF κ'_4

κ'_4	π ₁	π2	π3	π_4	π ₅
π1	0.0000	0.1301	0.0000	0.1975	-0.3036
π2	-0.8124	0.0000	-0.8124	-0.7496	-0.8673
π3	0.0000	0.1301	0.0000	-0.3133	-0.3036
π4	-0.3133	0.1201	0.0502	0.0000	-0.4363
π ₅	0.0486	0.1389	0.0486	0.0699	0.0000

κ' ₇	π_1	π2	π3	π_4	π_5
π1	0.0000	0.0920	0.1789	0.1389	0.0476
π2	-0.5405	0.0000	0.1535	0.1040	-0.4628
π3	-1.0510	-0.9014	0.0000	-0.6626	-1.0132
π4	-0.8158	-0.6110	0.1128	0.0000	-0.7665
π ₅	-0.2793	0.0788	0.1725	0.1305	0.0000

Table 17. The dominance degree of supplier π_x over supplier π_y concerning the CSF κ'_7

Table 18. The dominance degree of supplier π_x over supplier π_y concerning the CSF κ'_9

к'9	π1	π2	π3	π_4	π_5
π1	0.0000	0.0660	-0.3895	0.0411	0.1071
π2	-0.3895	0.0000	0.0000	0.0516	-0.4980
π3	0.0660	0.0000	0.0000	0.0516	0.0844
π4	-0.2427	-0.3046	-0.3046	0.0000	-0.4980
π ₅	-0.6322	0.0844	-0.4980	0.0989	0.0000

Table 19. The dominance degree of supplier π_x over supplier π_y concerning the CSF κ'_{12}

κ'_{12}	π_1	π2	π3	π_4	π_5
π1	0.0000	-0.2218	0.0838	0.0636	-0.2181
π2	0.0360	0.0000	0.0757	0.0524	-0.3110
π3	-0.5159	-0.4658	0.0000	-0.3362	-0.5601
π4	-0.3913	-0.3224	0.0546	0.0000	-0.4480
π ₅	0.0354	0.0505	0.0910	0.0728	0.0000

Table 20. The dominance degree of supplier π_x over supplier π_v concerning the CSF κ'_{14}

κ'_{14}	π_1	π2	π3	π_4	π_5
π1	0.0000	-0.6507	-0.6507	-0.7079	0.0430
π2	0.1168	0.0000	0.0000	-0.2789	0.1087
π3	0.1168	0.0000	0.0000	-0.2789	0.1087
π4	0.1271	0.0501	0.0501	0.0000	0.1196
π ₅	-0.2393	-0.6051	-0.6051	-0.6663	0.0000

Step 5. Generate the overall dominance matrix $\varphi'(\pi_x, \pi_y)$. Integrate dominance degree of supplier π_x over supplier π_y considering all CSFs, by using Eq. (18). This determines the overall dominance matrix of the suppliers $\pi_x(x = 1, 2, ..., 5)$ over suppliers $\pi_y(y = 1, 2, ..., 5)$. Table 21 presents these results.

	π_1	π2	π_3	π_4	π_5
π1	0.0000	-0.4840	-0.6869	-0.2201	-0.2554
π2	-2.1997	0.0000	-0.8456	-1.3603	-2.7702
π3	-1.9350	-1.1939	0.0000	-1.4619	-1.5703
π_4	-1.9203	-0.9792	-0.5088	0.0000	-1.9461
π ₅	-1.4850	-0.1309	-1.4826	-0.7999	0.0000

Table 21. The overall dominance degree of supplier π_x over supplier π_y

Table 21 shows that all the overall dominance degrees are less than zero. This shows the poor performance of each sustainable supplier compared to other sustainable suppliers under CSFs.

Step 6. Determine the overall values $\Phi(\pi_x)$ (x = 1, 2, ..., 5). Next, we apply Eq. (19) to transform the overall dominance degree (Table 21) into the overall values of each supplier $\pi_x(x = 1, 2, ..., 5)$ under 6 CSFs. Table 22 shows the results.

Table 22. The overall values of each supplier

Supplier	π1	π2	π3	π_4	π ₅
$\Phi(\pi_x)$	1.0000	0.0000	0.1835	0.3294	0.5927

Finally, we rank all the case study suppliers as $\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$. Sustainable supplier π_1 performs the best; the second-best sustainable supplier is π_5 , followed by π_4 , π_3 and π_2 . The overall values of sustainable suppliers π_1 and π_5 exceed 0.4. This indicates that these two sustainable suppliers are ranked higher than the others. There is a large gap between other suppliers and the suppliers π_1 and π_5 . Supplier π_4 is ranked third, and π_3 exhibits a smaller gap with the supplier π_4 . Suppliers π_4 , π_3 and π_2 have lower rankings.

Although each supplier has different levels of dominance and overall value, the overall level of sustainable development of potential suppliers is relatively low calculated by the proposed decision-making framework. From the perspective of social credit aspects, there is a tendency that enterprises pay more attention to social performance especially credit. So the outlook related to the sustainable development of suppliers is optimistic for China.

5. Discussions

In this section, we change values of parameters ζ and μ to observe the ranking results. Then we make comparative analysis including the decision-making framework without identifying CSFs and the decision-making framework with TOPSIS method.

5.1. Sensitivity analysis

The study proposes a new decision-making framework integrating DEMATEL as well as TODIM method based on PLTSs to make SSS under 6 CSFs. There exist parameter ζ and attenuation factor of the loss μ in Eq. (17) for calculating the dominance degree. Therefore,

it is necessary to analyze the influence of different values of parameters on the whole decision result.

In the calculation process, we set the value of ζ as 0.1. For verifying this method, we assign different values of 0.1, 0.01, and 0.001 to ζ to assess whether the supplier ranking changes. Table 23 shows that the ranking result of suppliers is consistently $\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$ corresponding to different values of ζ , and the best supplier are always π_1 . Similarly, we assign different values to the parameter μ , such as 1, 2 and 3. Also, the supplier ranking remain unchanged when the value of μ changes.

From the analysis (Tables 23 and 24), the ranking results of potential sustainable suppliers are not sensitive to the changes of parameters. This displays that the parameters ζ and μ are without loss of generality, and the values we assign to the two parameters also remain generality. This indicates the robustness as well as the validity of our proposed framework.

ζ	Sorting
0.1	$\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$
0.01	$\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$
0.001	$\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$

Table 23. The sorting results for different values of $\boldsymbol{\zeta}$

Table 24. The sorting results fo	r different values of μ ($\mu > 0$)
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μ	Sorting
1	$\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$
2	$\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$
3	$\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$

5.2. Comparative analysis

In this section, we conduct comparative analysis including decision-making framework without identifying CSFs as well as decision-making framework with TOPSIS method for verifying our framework's conciseness and effectiveness.

5.2.1. Decision-making framework without identifying CSFs

To verify the effectiveness and conciseness of the decision-making framework, we collect the evaluation of five potential suppliers under 15 factors. Then we transform the evaluation in the form of linguistic term into matrices of PLTSs and normalize them. In order to obtain 15 factors' weights, we calculate the factors' casual degree E_i , which stands for the influence between factors and factor systems. And we adopt $V_{ij} = |E_i| / \sum_{i=1}^n |E_i|$ to make all factors have positive casual degree for better reflecting the variation of factors. Next, the initial weights of 15 factors are obtained by combining entropy weight method and DEMATEL methods

of 15 factors are obtained by combining entropy weight method and DEMATEL methods on the basis of PLTSs. Finally, the new dominance degree is calculated based on standard relative importance degree, and then the potential supplier is ranked. The results are shown in the Tables 25 and 26.

Supplier	π_1	π2	π3	π_4	π ₅
π1	0.0000	-1.5538	-0.0079	-1.0410	-1.4366
π2	-14.9799	0.0000	-6.0382	-5.9552	-14.0438
π3	-13.4783	-3.8533	0.0000	-6.1121	-9.9524
π_4	-13.3861	-1.9817	-5.4436	0.0000	-11.3529
π ₅	-6.6670	-0.5130	-4.4296	-1.5723	0.0000

Table 25. The overall dominance degree of supplier π_x over supplier π_y under 15 factors

Supplier	π1	π2	π3	π_4	π ₅
$\Phi(\pi_x)$	1.0000	0.0000	0.2061	0.2394	0.7528

As can be seen from Table 26, the ranking result of potential suppliers in the framework without identifying CSFs is: $\pi_1 \succ \pi_5 \succ \pi_4 \succ \pi_3 \succ \pi_2$. This calculated result under more factors is similar with our proposed decision-making framework. Thus it verifies that our decision-making framework for identifying CSFs with DEMATEL is much simpler because fewer factors are used but the same decision results are obtained. Therefore, the framework we proposed in this paper is concise while ensuring accuracy.

5.2.2. Decision-making framework with TOPSIS method

TOPSIS method is commonly used in practical decision making and it has also integrated with the PLTSs. As a MADM method, we select the TOPSIS method to for constructing the other framework to make comparative analysis in this section.

According to the above decision-making framework, we construct another framework consisted of DEMATEL and TOPSIS methods to make SSS for NEV Company. Probabilistic linguistic evaluations of five alternative suppliers under identified CSFs are adopted. Then, we calculate the initial standard relative degree (SI(L(p)) for each alternative supplier using Eq. (5) (Table 27). In line with Table 27, we obtain the maximum max SI(L(p)) and minimum mix SI(L(p)) for each CSF.

SI(L(p))	π1	π2	π3	π_4	π ₅
κ'1	0.2722	0.3333	0.3220	0.2854	0.2434
κ'4	0.2434	0.1377	0.2434	0.2277	0.2582
κ'7	0.2854	0.2357	0.0974	0.1721	0.2722
κ'9	0.2177	0.2434	0.2434	0.2277	0.2854
κ' ₁₂	0.1822	0.2582	0.2582	0.2722	0.1925
κ' ₁₄	0.2357	0.2277	0.1925	0.2108	0.2434

Table 27. Standard relative degree of importance SI(L(p)) of each sustainable supplier

	π_1	π2	π3	π_4	π_5
$\max SI(L(p))$	0.2854	0.3333	0.3220	0.2854	0.2854
$\min SI(L(p))$	0.1822	0.1377	0.0974	0.1721	0.1925

Table 28. The maximum max SI(L(p)) and minimum min SI(L(p)) of each supplier

After generating Tables 27 and 28, we propose the new degree of deviation between the *SI* (*L*(*p*)) of sustainable supplier π_r (*r* = 1,2,...,5) and max *SI* (*L*(*p*)):

$$\begin{split} \Delta(\pi_r, \max SI(L(p))) &= \sum_{\lambda=1,2,4,9,10} w_\lambda \Delta \ (SI(L(p)), \ \max SI(L(p))) = \\ \sum_{\lambda=1,2,4,9,10} w_\lambda (\sqrt{\frac{(\max SI(L(p)) - SI(L(p)))^2}{\#L(p)}})^3, \end{split}$$

#L(p) is the number of a probabilistic linguistic terms in the NPLTSs matrix.

Similarly, the degree of deviation in the *SI* (*L*(*p*)) of sustainable supplier π_r (*r* = 1,2,...,5) and the min *SI* (*L*(*p*)) is defined as:

$$\Delta(\pi_{\rm r},\min SI(L(p))) = \sum_{\lambda=1,2,4,9,10} w_{\lambda} \Delta \ (SI(L(p)),\min SI(L(p))) = \sum_{\lambda=1,2,4,9,10} w_{\lambda} (\sqrt{\frac{(SI(L(p)) - \min SI(L(p)))^2}{\#L(p)}})^3.$$

Furthermore, according to Pang et al. (2016), the closeness coefficient of each sustainable supplier in this paper is described as:

$$C(\pi_r) = \frac{\Delta(\pi_r, \min SI(L(p)))}{\max \Delta(\pi_r, \min SI(L(p)))} - \frac{\Delta(\pi_r, \max SI(L(p)))}{\min \Delta(\pi_r, \max SI(L(p)))},$$

where $C(\pi_r) \le 0$ (r = 1, 2, ..., 5), max $\Delta(o_r, \max SI(L(p)))$ is the biggest degree of deviation between the sustainable supplier π_r and max SI(L(p)), and max($\pi_r, \max SI(L(p))) = \max_{1 \le r \le 5} \Delta(\pi_r, \min SI(L(p)))$. The term min $\Delta(\pi_r, \max SI(L(p)))$ represents the smallest degree of deviation between the sustainable supplier π_r and max SI(L(p)), and min($\pi_r, \max SI(L(p))$) = min_{1 \le r \le 5} $\Delta(\pi_r, \max SI(L(p)))$.

Finally, we rank the five suppliers according to the calculated closeness coefficient $C(\pi_r)$ according to Table 29. We generate a new ranking of the sustainable performance of the 5 NEVs suppliers: $\pi_1 \succ \pi_3 \succ \pi_5 \succ \pi_4 \succ \pi_2$.

$\Delta (\pi_r, \min SI) (L(p)))$	$\Delta (\pi_r, \max SI) (L(p)))$	$C(\pi_r)$	Ranking
0.00026	0.00004	-0.02903	1
0.00011	0.00006	-1.14143	3
0.00005	0.00023	-5.67167	5
0.00004	0.00006	-1.39054	4
0.00024	0.00004	-0.05562	2

Table 29. Closeness coefficients

From the ranking results of two methods, the comparison reveals that the optimal sustainable supplier is π_1 and the worst is π_2 , which the same outcomes are as the result obtained using the preamble framework. This indicates the validity of the proposed decision-making framework. However, there are differences in the ranking of suppliers π_3 , π_4 and π_5 . Supplier π_3 performs worse than π_4 , π_5 using the proposed framework. In contrast, π_3 performs better than π_4 , π_5 using the comparative framework. In order to further explain the rationality of the proposed framework, we introduce the concept of score function $E(L(p)) = \sum_{k=1}^{\#L(p)} r^{(k)} p^{(k)} / \sum_{k=1}^{\#L(p)} p^{(k)}$ (Pang et al., 2016), which is used to compare PLTSs with each other. Take supplier π_3 , π_5 for example, according to Table 13, we get the sum score value of supplier $\pi_3 \sum E(L(p)) = [(0 \cdot 2 + 2 \cdot 0.2 + 3 \cdot 0.8) + (0 \cdot 0 + 0 \cdot 0.2 + 2 \cdot 0.8)]$ + $(0 \cdot 0.2 + 1 \cdot 0.6 + 2 \cdot 0.2) + (\overline{(-3)} \cdot 0.2 + (-2) \cdot 0.6 + 0 \cdot 0.2)]/1 + [(0 \cdot 0.6 + 0 \cdot 2 + 2 \cdot 0.2) + ((-1) \cdot 0.2 + 2 \cdot 0.4 + 3 \cdot 0.2)]/0.8 = 5.2$, and the sum score value of supplier $\pi_3 \sum E(L(p)) = E(L(p))$ $[(0 \cdot 1 + 0.4 \cdot 1 + 2 \cdot 0.6) + ((-1) \cdot 0.4 + 2 \cdot 0.4 + 3 \cdot 0.2) + ((-3) \cdot 0.2 + 1 \cdot 0.2 + 2 \cdot 0.6) + ((-1) \cdot 0.4 + 2 \cdot 0.4 + 3 \cdot 0.2) + ((-3) \cdot 0.2 + 1 \cdot 0.2 + 2 \cdot 0.6) + ((-1) \cdot 0.4 + 2 \cdot 0.4 + 3 \cdot 0.2) + ((-3) \cdot 0.2 + 1 \cdot 0.2 + 2 \cdot 0.6) + ((-3) \cdot 0.2 + 2 \cdot 0.2 + 2 \cdot 0.2) + ((-3) \cdot 0.2 + 2 \cdot 0.2 + 2 \cdot 0.2) + ((-3) \cdot 0.2) + ((-3) \cdot 0.2 + 2 \cdot 0.2) + ((-3) \cdot 0.2 + 2 \cdot 0.2) + ((-3) \cdot 0.2) + ((((-2) \cdot 0.2 + 0 \cdot 0.2 + 3 \cdot 0.6) + (1 \cdot 0.6 + 2 \cdot 0.2 + 3 \cdot 0.2) + ((-1) \cdot 0.6 + 0 \cdot 0.2 + 2 \cdot 0.2]/1 = 5.8.$ Apparently, the experts' evaluation of supplier π_5 is better than supplier π_3 . It proves that the proposed decision-making framework composed of TODIM method is more effective than the framework with TOPSIS method for SSS. The main reason for this difference is that the TOPSIS approach does not consider the influence of experts' psychology.

Conclusions

The suitable sustainable supplier helps enterprise realize healthy and steady development. This paper proposes a new decision-making framework for SSS. Firstly, we reconstruct a new factor system considering social credit under the circumstance that the Chinese government intensifying efforts to build a national credit system. Secondly, this paper innovatively proposes the relative importance degree, standard relative importance degree, deviation of importance degree, and influence degree to measure the interactive influence between factors based on PLTSs. Then we combine PLTS and DEMATEL to identify the CSFs. Thirdly, we combine entropy weighting method with DEMATEL method to compute CSFs' weights. Fourthly, we adopt TODIM method to combine with PLTS, DEMATEL, and entropy weighting method for constructing the new decision-making framework. Also, the case study of a NEV company is applied to make numerical calculation. Finally, sensitivity analysis and comparative analysis are conducted. In comparative analysis, we not only make comparison with decision-making framework without identifying CSFs, but also the decision-making framework with TOPSIS method. The analysis verifies the stability and effectiveness of the proposed decision-making framework.

In the future, we will try to construct a more detailed factor system for enterprises to refer, such as the more detailed perspectives and the more detailed analysis of social status. Combining with text mining, the problem of large-scale group decision-making in sustainable supplier selection with expert consensus is the content of our future research. In terms of the decision-making framework, we design and implement it from the perspective of the enterprise's choice of sustainable suppliers, and the subsequent research should explore its contribution to the overall sustainable development in reality.

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Author contributions

Yuanxiang Dong and Xumei Zheng conceived the study and were responsible for the design and development of the data analysis. Weijie Chen, Hongbo Shi, and Ke Gong were responsible for data collection and analysis. Xumei Zheng wrote the first draft of the article. Yuanxiang Dong, Weijie Chen as well as Ke Gong was responsible for supervision and funding acquisition. Zeshui Xu confirmed the content of the entire research design.

Disclosure statement

The authors declare that there is no conflict of interest regarding the publication of this paper.

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