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A Multi-Criteria Decision-Making Framework for Sustainable Supplier Selection in the Circular Economy and Industry 4.0 Era

Ziyuan Xie [1], Guixian Tian [2,*] and Yongchao Tao [3]

[1] College of Finance & Information, Ningbo University of Finance& Economics, Ningbo 315175, China
[2] School of Business, Pingxiang University, Pingxiang 337055, China
[3] Shandong Marine Economic and Cultural Research Institute, Shandong Academy of Social Science, Qingdao 266000, China
* Correspondence: 16010039@pxu.edu.cn

Abstract: Supplier selection is a difficult and important issue in sustainable supply chain management. This research proposes a managerial framework based on Industry 4.0, a plan for evaluating and choosing sustainable suppliers to implement circular economy practices. Green supplier selection (GSS), the circular economy, and Industry 4.0 have become hot topics in recent operations management discussions. Three main categories (e.g., economic, environmental, and social) and 16 subcategories related to supplier selection decisions were identified using a hybrid approach combining literature reviews and industry expert opinions. In the fuzzy environment of Pythagorean, this paper proposes comprehensive techniques for the selection of green suppliers based on entropy, stepwise weighted assessment ratio analysis (SWARA), and complex proportional assessment (COPRAS) methods. To calculate the standard weight, this technique first merges the objective weight found by the entropy method and the subjective weight found by the SWARA method. The findings show that access to finance and financial availability for implementing Industry 4.0 within the circular economy (ECO5) and R&D in environmental issues using Industry 4.0 technologies (ENV7), Information technology (IT) facilities (ECO6), and Product cost/price (ECO1) showed highest ranking among sub-criteria. Moreover, Supplier 5 was listed as the best sustainable supplier when they started making such a decision. The results of the proposed method help decision-makers make effective and efficient sustainable supplier selection.

Keywords: green supplier selection; circular economy; Industry 4.0; SWARA-COPRAS method

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1. Introduction

The current COVID-19 pandemic has devastated our lives in many ways [1–4]. In this regard, selecting a supplier is an important responsibility of the organization and the factory's overall supply chain strategy [5]. The decision to choose a supplier is a strategic one that aids organizations in reducing costs and risk, achieving superior services and high-quality products [6,7]. Providing the services or product in the right quality or condition at the right point in time, the right quantity at the right place, and the right price from the right supplier is the responsibility of the procurement department in any supply chain [8–10]. The selection of the most appropriate supplier is the most important factor in achieving supply chain performance [11]. As stakeholders' awareness and interests in sustainability has grown, businesses and factories have begun to incorporate sustainability concerns into their sustainable products and supply chain operations [12]. When selecting sustainable suppliers, integrating and considering social [13,14], environmental, and economic criteria is one way to achieve sustainability goals.

Advanced technology significantly impacts our society [15,16]. This digital revolution, also known as the digital economy, has aided in knowledge transfer [17], information sharing [18–20] and communication [21] between various players in the supply chain network. Moreover, production flexibility [22], customized demand [23], shorter product life cycles, efficient and effective resource utilization necessitate an industrial revolution in manufacturing and supplier selection [24]. Furthermore, a responsive manufacturing system is required for a shorter product life cycle, which can only be achieved through advanced technology [18].

In industrial papers and recent literature [11,25–28], Industry 4.0 has been primarily discussed from the standpoint of production as an operational outlook. On the other hand, Industry 4.0 and its supporting technology are thought to have the potential to affect every aspect of organizations and factories [29] and significantly improve managerial disciplines such as logistics management and supply chain [30,31]. The steady rise in business system automation, as well as the resulting productivity gains, efficiency, and the quality enhancement is encouraging organizations to implement the Industry 4.0 operational perspective in other areas of their organizations, like supply chain management [32,33]. By leveraging data analytics, Industry 4.0 and the current industrial revolution make supply chains robust to internal and external disruptions [34,35]. Furthermore, it aids in reducing inventory and enhancing customer service [36,37]. Industry 4.0 enables better monitoring and participation of local supply chains, resulting in more sustainable supply chains.

The circular economy and Industry 4.0 are two relatively new concepts that have been successfully implemented in the perspective of a sustainable supply chain (SSC). The circular economy concept was recently unveiled, focusing on environmental and socioeconomic issues to convert non-value-added wastes into value-added resources [38]. In order to gain a competitive advantage, suppliers must be chosen carefully for sustainable supply chain management. Multiple criteria, such as such as quality, price, labor relations, flexibility, and capability, are applied in the selection of suppliers [39]. The selection process for suppliers has changed dramatically in current years as a result of the effect of Industry 4.0 and digital technologies on the supply chain. According to the Industry 4.0 implementation process, companies are willing to require new conditions for their particular suppliers. Suppliers are also looking for the integrated approach and Industry 4.0 in order to meet various customer requirements [40]. From the perspective of Industry 4.0, there are limited studies on supplier evaluation. In order to reap the advantages of integrating circular economy and Industry 4.0 into green supplier selection, organizations must coincide their decision and supplier selection processes within the context of Industry 4.0 and circular economy. To help close the literature gap and advance practical and theoretical understanding, this study introduces an Industry 4.0 criteria framework for the selection of green suppliers based on the circular economy. The research examines this framework in the context of the Chinese agri-based manufacturing industry, providing practical insights and implementation guidelines. As a result, the goals of this paper are to develop a green supplier selection criteria framework by identifying and refining circular economy-based Industry 4.0 initiatives within the procedures of a sustainable supply chain. In addition, a group of suppliers is evaluated and ranked using the proposed framework for an integrated circular economy initiative based on Industry 4.0.

Choosing the right supplier is critical to a company's success in the global market and the enhancement of its competitive advantage. There is a lack of literature that considers applications of Industry 4.0 in the selection of suppliers, even though there is abundant research on supplier selection. The proposed method was used to choose the best supplier in the advanced textile industry using the Industry 4.0 policy from the circular economy perspective. The case company selected in this study intended to invest heavily in innovative technologies in order to gain a competitive advantage and reduce production costs in the international market. Implementation of the Industry 4.0 approach has begun for this purpose and has been applied to a real-world textile supplier selection problem. As a result, this study recommended an integrated MCDM method for selecting the best supplier for the textile manufacturer. The following summarizes the originality of this paper: (1) This is the first study to take into account Industry 4.0 elements in the selection of suppliers in a fuzzy environment. This research differs significantly from the other supplier selection problem, which considers industry 4.0 and traditional criteria. (2) A hybrid MCDM approach was proposed (3) For the agri-based manufacturing industry, a real case study was conducted. This paper demonstrated how the Industry 4.0 framework influences supplier choices within the industry and other industries that follow the GSS standards. (4) For the first time in the literature, new integrated entropy, WPSA, and COPRAS techniques are applied. As a result, the COPRAS technique applied a ranking system for the options based on their utility and importance levels.

This study has been structured as follows. The literature for this study and its framework has been discussed in Section 2. Section 3 consists of the theoretical and empirical framework of the study. In Section 4, case studies and findings are presented, and Section 5 covers the discussion and conclusions of the paper.

2. Theoretical Framework and Literature Review

In recent years, researchers and practitioners from a variety of disciplines have examined how businesses can integrate environmental concerns into their operations through the use of theoretical frameworks such as ecological foot printing [41], triple-bottom-line [42], industrial ecology [43], eco-efficiency [44], and life cycle management [45]. These theoretical frameworks provide useful insights for business leaders seeking to balance environmental, economic, and social problems in their company models. The many theoretical frameworks are not mutually exclusive but rather explain diverse aspects of the same reality. As a result, socioeconomic and environmental stewardship are not defined by a single theory but rather by a collection. Our study adheres to a coherent theoretical framework discourse, namely Ecological Modernization Theory (EMT), resulting from these arguments [46]. The EMT hypothesizes that environmental issues arising from economic development may be mitigated by increasing resource efficiency through technological innovation, such as green supply chain techniques that improve a firm's environmental and economic performance. Ecological conservation, in this context, is no longer a "problem" but an "opportunity" [46], which supports the concept of "ecologizing economy" and "economizing ecology" [47]. This study developed an all-inclusive MCDM framework on the theoretical foundations of EMT.

2.1. Industry 4.0 and Circular Economy

Researchers, practitioners, and academics have progressively viewed circular economy practices, and Industry 4.0 technologies in recent years are the most relevant industrial concepts [34]. The circular economy has long been recognized as a broad concept that encompasses the integration of environmental welfare into economic activity by implementing a regenerative or restorative economic system [48]. This is accomplished by deliberately replacing the end-of-life impression with restoration and closing the loop of the linear product lifecycle. The circular economy concept is applied to achieve sustainability by reusing material and removing waste and lethal materials, despite some conceptual limitations [49]. According to [50], the circular economy may not be the ultimate goal but rather part of a larger strategy to improve the effectiveness and efficiency of resources. Industry 4.0, on the other hand, refers to business systems that are driven by information technologies [36]. Table 1 presents the circular economy and Industry 4.0 features. A dramatic rise in new Industry 4.0 technologies, such as the Internet of Things (IoT), Blockchain Technology (BCT), and big data analytics (BDA), has triggered this new age industry. Industry 4.0 provides huge information for foreseeing failure, policymaking, interconnectivity, and accepting the changes by providing data ubiquity [51]. In addition, I4.0 enables improved cyber-machine interactions, shorter product development times, a human-machine interface, and greater product customization, all of which contribute to the creation of high-quality products at lower costs. These advantages open up a growing number of new possibilities for developing and implementing improvement strategies.

Table 1. Identification of Industry 4.0 and circular economy features.

Reference	Method	Industry 4.0 and Circular Economy Features	Case Example
(Gul and Ak 2018) [52]	FTOPSIS, PFAHP	Rejection rate, Cost/price, delivery delay, Industry 4.0 technology	-
(Gul 2018) [53]	FVIKOR	cognitive computing, IoT, cloud computing, Cyber-Physical Systems (CPS)	A cement factory
(Ghadimi et al., 2019) [54]	Multi-Agent Systems (MASs) approach	Customer, Leadership, operation, product, culture, governance, people, technology, organization, and quality	Manufacturing firms
(Gupta et al., 2019) [55]	AHP, WASPAS and TOPSIS	Selective waste collection, product life cycle, waste sorting, product assembly, product selling, product printing, waste treatment	Automotive industry
(Dev et al., 2019) [51]	Rough-fuzzy DEMATEL-TOPSIS	Green purchasing, green design, green manufacturing, green and smart logistics, internal management awareness	A case study in new energy vehicle transmission
(Das et al., 2020) [56]	Single-valued neutrosophic numbers	3D printing, automated guided vehicles, robotics	Automotive sector
(Banaeian et al., 2018) [57]	TOPSIS, VIKOR, and GRA methods	Big data, Additive manufacturing, cloud computing, autonomous robots, augmented reality, automatic vehicles, blockchain, cybersecurity, IoT, and artificial intelligence	Agri-food industry
(Chen et al., 2020) [58]	TOPSIS and Multi-Choice Goal Programming, Decision Support System,	traceability, Digitalization, supplier's resource flexibility, agility, supply chain density, cybersecurity risk management, re-engineering, automation disruption, supply chain complexity, supply chain visibility, and information management, supplier reliability	Hypothetical case study
(Hasan et al., 2020) [59]	Fuzzy based TOPSIS method	Supply chain flexibility, Supply chain integration, intelligent inventory control, visibility through channels, communication, customer focus level, supply chain security, lead time improvement	Textile industry
(Çalık 2021) [60]	Pythagorean fuzzy AHP and fuzzy TOPSIS	Real-time capabilities and interoperability, virtualization, service orientation, cost of the recycled-material supplier, decentralization	Agricultural tools and machinery company

Table 1. *Cont.*

Reference	Method	Industry 4.0 and Circular Economy Features	Case Example
Summary		Industry 4.0 technology, network physical system, selective waste collection, green procurement, green intelligent logistics, internal management awareness, supply chain flexibility, cost of recycled materials suppliers	/

The amalgamation of circular economy practices and Industry 4.0 technology are becoming increasingly necessary in the industrial context. According to [28], data discrepancies from various sources impede the transformation of a linear supply chain into a circular supply chain. [61] explored that today's businesses require the discernibility, resilience, and flexibility that Industry 4.0 provides in order to avoid the failure of sustainable recycling, reusing, remanufacturing, and operations. As a result, recent research has found that technology like Industry 4.0 can open the way for circular economy practices [6], for example, suggested following up on products after they were used to recover components. Likewise, [37] stated that Industry 4.0 technology aid in the efficiency of circular economy practices, resulting in better financial outcomes.

In addition, a suitable set of criteria must be identified to fully implement Industry 4.0 technology into the circular economy's practices in the green supplier selection process [62]. Many studies on green supplier selection have been published, but none of them explicitly take into account the use of Industry 4.0 technology initiatives in the integration of the circular economy [11]. Identifying Industry 4.0 criteria based on circular economy practices is crucial in the selection process because it lays the groundwork for selecting the best supplier. The majority of previous GSS related studies relied heavily on the traditional environmental, economic and social aspects of sustainability to make their decisions [63]. Organizations and policymakers must now consider all of these aspects of sustainability when making decisions in light of the emergence of circular economy trends and the 4th industrial revolution. As a result, green procurement decisions must incorporate criteria related to Industry 4.0 and circular economy practices. For the first time, a unified framework based on circular economy practices is used in this study to implement Industry 4.0 technology for SSC operations for the first time.

2.2. Sustainable Supply Chains Management (SSCM)

Companies worldwide are being asked to fulfill a more competitive economy [64]. Sustainability is one of the most important goals as environmental degradation and social inequality rise. As a result, operationalizing sustainability necessitates a major shift from profit maximization toward companies' environmental performance and social objectives [65]. Throughout their supply chains, companies recognize the importance of sustainability [66]. Because the product is considered throughout the supply chain, from the initial processing of natural resources to the enduser, bringing attention to them is a step toward broader sustainability adoption [19,67]. As a result, more sustainable practices and the facilitation of more sustainable behavior in SCs are required for sustainable supply chain management (SSCM) [68]. SSCM aims to reduce waste, reduce negative environmental effects, and save money across the supply chain. According to the definition of SSCM, "The management of material, information, and capital flows as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, i.e., economic, environmental, and social, into account," ([69] (p. 1700)). SSCM considers the triple-bottom-line (TBL) parameters of social, environmental, and economic sustainability during the planning of supply chain decisions.

Stricter government policies, social activism, raising public awareness, pressures, organization image, corporate brand, and customer pressures all drive sustainability integration into supply chains [70]. Sustainability has also been incorporated into the supply chains of businesses and factories to manage supply chain risks like labor disputes and environmental damage, which can cause supply chain disruptions [71]. Suppliers' operations can negatively influence the buying firms' reputations or even cause severe supply chain disruptions [72]. Employee strikes by suppliers, accidents, legal disputes, spills, natural disasters, and other events can negatively influence the product image of the buying firm and the buying firm's financial health in the form of lost sales and other factors [73]. To increase the overall sustainability of the supply chain, both buying and supplying firms in a coordinated manner must manage and integrate sustainability into their business operations. To advance and upscale the goal of achieving sustainable supply chains, multinational organizations are expected to expand their efforts in sustainability.

The research status of sustainable supply chain management is summarized in Table 2.

Table 2. Literature summary of sustainable supply chain management.

Author	Content	Time
Seuring and Müller [69]	Consider the three goals of sustainable development: economy, environment and society	2008
Koberg and Longoni [70]	Policy support, social behavior and corporate image will promote the integration of sustainable development into the supply chain	2019
Majumdar and Sinha [71]	Sustainability to manage supply chain risk	2019
Bor [73]	Emergencies and disasters will affect the company's image and financial health	2021

2.3. Green Supplier Selection and Industry 4.0

Green supplier selection (GSS) has become increasingly important in supply chain (SC) performance in recent years and is critical for any organization [74]. GSS has piqued the interest of many researchers and practitioners in recent years and is now regarded as a priority issue [55]. In the literature, a number of researchers have examined GSS as a key decision in SSCM. Previously, GSS research focused primarily on environmental and economic sustainability criteria. Recent studies [75], on the other hand, have begun to consider sustainability from a TBL perspective when making sourcing decisions. Using all three sustainability dimensions (TBL) improves an organization's sustainability performance while lowering operational risks. [76] emphasized the importance of selecting suppliers based on all aspects of sustainability. Furthermore, [77] investigated that the GSS model should include not only the economic and green aspects but also the broadening TBL sustainability concept. On the other hand [78], pointed out that the literature is scarce on integrating quantitative and qualitative sustainability criteria in GSS.

Several authors have recently developed a number of quantitative models that focus on environmental and economic sustainability [67,79]. Many authors have begun to create quantitative techniques that take into account environmental and social factors [49]. GSS models have all used integrated methods, such as the AHP-Entropy-TOPSIS, the DEMATEL-TOPSIS, and the AD-AHP. Granular computing techniques have been used to solve MCDM problems in recent years. However, exact or real data are inadequate and insufficient to address real-world issues in many practical situations. Ref. [80] invented the fuzzy set doctrine, which is a generalization of the classical set doctrine, and each object in the fuzzy set doctrine is assigned a membership value. Several studies have suggested the use of structures such as fuzzy sets in MCDM in response to such ambiguity and complexity [55,81,82]. In addition to each object's membership function in a traditional fuzzy set, the non-membership function is assigned to each object by the intuitionistic fuzzy set. Then the interval-valued intuitionistic fuzzy sets (IVIFSs) were presented [83], which are an extended form of IFSs. IVIFSs and IFSs can be used to investigate a wide range of problems involving uncertainty, which includes MCDM issues.

Zhuang et al. [84] introduced COPRAS, a new decision-making method that effectively deals with MCDM issues. The COPRAS has three main features: (1) It compares the ratios of the best and worst solutions at the same time. (2) It generates results in a relatively short time than other MCDM techniques do. (3) It is very easy and simple to understand. The application of the classic COPRAS method has been the subject of several studies. Under these circumstances, researchers were persuaded to extend the COPRAS method as a result of the inherent uncertainty in weights and attribute value. Mubarik et al. [76] used ANP and fuzzy COPRAS to create the latest hybrid model for estimating working approaches to resolve the issue of hesitant fuzzy soft decision-making, Yu and Huo [79] developed Weighted Aggregated Sum Product Assessment (WASPAS), Complex Proportional Assessment (COPRAS) and Multi-Attributive Border Approximation Area Comparison (MABAC). In current years, the COPRAS technique has become widely used in a vast range of decision-making situations.

In recent years, a large number of studies have made relevant research on the selection decision of green and sustainable suppliers. In order to better understand their research status, the representative literature in recent years are summarized as shown in Table 3.

Table 3. Literature summary of green supplier selection.

Author	Content	Time
Yazdani [77]	The selection of green suppliers should include the concepts of economy, green and sustainability	2017
Gupta [55]	Quantitative technology of economic sustainability considering environmental and social factors	2021
Zhang [80]	Invented fuzzy set theory	2020
Zhuang [84]	Introduce COPRAS to solve the MCDM problem	2021
Mubarik [76]	Combining ANP and fuzzy COPRAS to solve the fuzzy soft decision problem	2021

To sum up, in recent years, research on enterprise supply chain and green sustainable supplier selection has been increasing, and most of the research is to achieve decision-making in green sustainable supplier selection. However, it can still be seen from the existing research that few studies take into account the current situation of circular economy in economic development, so it is difficult to cater to social change in the decision-making process. In this study, we analyzed the multi-criteria decisionmaking of sustainable supplier selection in the era of circular economy and Industry 4.0, and expected to provide theoretical support for the development of Industry 4.0.

3. Methodology

3.1. Empirical Framework

The literature extends the conventional complex proportional assessment (COPRAS) approach to interval-valued fuzzy sets (IVFSs), Pythagorean fuzzy set, fuzzy sets, interval-valued intuitionistic fuzzy sets (IVIFSs), interval type-2 fuzzy sets, hesitant fuzzy set, hesitant fuzzy linguistic sets, and hesitant fuzzy soft sets. To explain the multi-criteria decision-making (MCDM) problems under a hesitant fuzzy set, Ref. [85] presented an analytical COPRAS. Ref. [86] presented an integrated model based on AHP-COPRAS for assessing the digital supply chain partner selection problem in a Pythagorean fuzzy environment. Keshavarz Ghorabaee et al. [87] pioneered an integrated COPRAS-based methodology for determining project critical paths. Balali et al. [88] used the entropy technique to estimate a Pythagorean fuzzy COPRAS method with calculated weights. According to existing research, the COPRAS method with a Pythagorean fuzzy set based on SWARA and entropy measure method has yet to be generalized and specifically applied to selecting green suppliers.

The COPRAS preference-ranking method assumes that the significance and utility degree of the available alternatives are directly and proportionally dependent on each other in the presence of mutually conflicting criteria and that the significance and utility degree of the available alternatives are proportionally dependent on each other. When comparing alternatives, it takes into account how well they perform in terms of various criteria as well as the weights assigned to those criteria. By considering both the ideal and the ideal-worst solutions, this method is able to select the best decision possible. To evaluate and select alternative materials for the given engineering problems, the COPRAS method is used. This method employs a stepwise ranking and evaluating procedure of the alternatives in terms of their significance and utility degree. This method has already been successfully used to solve a variety of problems in the construction industry.

Definition 1. *A fuzzy Pythagorean set U in a finite universal set $X = \{x_1, x_2, \ldots, x_t\}$ can be defined as*

$$U = \{\langle x_l, U(t_U(x_l), f_U(x_l))\rangle | x_l \in X\}.$$

where $t_U : X \to [0,1]$ *and* $f_U : X \to [0,1]$.

It describes the degree of non-belongingness and belongingness of an object $x_l \in X$ to U. it satisfies the constraint $0 \le (t_U(x_l))^2 + (f_U(x_l))^2 \le 1,\ l = 1, 2, \ldots, t.$

The hesitancy degree is defined by $\pi_U(x_l) = \sqrt{1 - t_U^2(x_l) - f_U^2(x_l)}$, for each $x_l \in X$. Further, Rani et al. [89] labelled $(t_U(x_l), f_U(x_l))$ as a Pythagorean fuzzy number represented by $\beta = (t_\beta, f_\beta)$, where $t_\beta, f_\beta \in [0,1]$ and $0 \le t_\beta^2 + f_\beta^2 \le 1$.

Definition 2. *Suppose a fuzzy Pythagorean number $\beta = (t_\beta, f_\beta)$, then $\hbar(\beta) = (t_\beta)^2 + (f_\beta)^2$ and $S(\beta) = (t_\beta)^2 - (f_\beta)^2$ are referred to as the accuracy and score functions of β, where $\hbar(\beta) \in [0,1]$ and $S(\beta) \in [-1,1]$. As a result, Definition 3 can describe an improved score function $S(\beta) \in [-1,1]$ for Pythagorean fuzzy numbers β.*

Definition 3. *Consider $\beta = (t_\beta, f_\beta)$ being a Pythagorean fuzzy number*

$$S^*(\beta) = \frac{1}{2}(S(\beta) + 1)$$

$$\hbar^\circ(\beta) = 1 - \hbar(\beta),$$

where $\hbar^\circ(\beta) \in [0,1]$ and $S^*(\beta)$ indicate the uncertainty functions and improved score of β. For any two Pythagorean fuzzy numbers, $\beta_1 = (t_{\beta_1}, f_{\beta_1})$ and $\beta_2 = (t_{\beta_2}, f_{\beta_2})$: if $S^*(\beta_1) > S^*(\beta_2)$, then $\beta_1 > \beta_2$, if $S^*(\beta_1) = S^*(\beta_2)$, then if $\hbar^\circ(\beta_1) > \hbar^\circ(\beta_2)$, then $\beta_1 > \beta_2$, and if $\hbar^\circ(\beta_1) > \hbar^\circ(\beta_2)$, then $\beta_1 = \beta_2$.

Definition 4. *Let $\beta = (t_\beta, f_\beta)$, $\beta_1 = (t_{\beta_1}, f_{\beta_1})$ and $\beta_2 = (t_{\beta_2}, f_{\beta_2})$be the pythagorean fuzzy numbers. The operations on pythagorean fuzzy numbers are then presented as*

$$\beta^c = (t_\beta, F_\beta);$$

$$\beta_1 + \beta_2 = \left(\sqrt{t_{\beta_1}^2 + t_{\beta_2}^2 - t_{\beta_1}^2 t_{\beta_2}^2}, f_{\beta_1} f_{\beta_2}\right);$$

$$\beta_1.\beta_2 = \left(t_{\beta_1} t_{\beta_2}, \sqrt{f_{\beta_1}^2 + f_{\beta_2}^2 - f_{\beta_1}^2 f_{\beta_2}^2}\right);$$

$$\lambda\beta = \left(\sqrt{1 - \left(1 - t_\beta^2\right)^\lambda}, (f_\beta)^\lambda\right), \lambda > 0;$$

$$\beta^{\lambda} = \left(\left(t_{\beta} \right)^{\lambda}, \sqrt{1 - \left(1 - f_{\beta}^2 \right)^{\lambda}} \right), \lambda > 0.$$

3.2. Entropy Measure for Pythagorean Fuzzy Sets

The calculation of entropy is very good at displaying and capturing favorable and advantageous features in fuzzy sets and their extensions. In the perspective of fuzzy sets, Ref. [90] offered a non-probabilistic entropy. For FSs, IFSs, IVIFSs, and HFSs, a variety of entropy measures are currently used [91,92]. Sharma et al. [93] presented and discussed various measures (inclusion, entropy, similarity, and distance measures) for PFSs. In the Pythagorean fuzzy WASPAS method, Teerawattana and Yang [94] proposed using divergence and Pythagorean fuzzy entropy measures to determine the criteria weights. Alipour et al. [95] went on to extend the idea of fuzzy entropy for Pythagorean fuzzy sets (PFSs) by introducing a number of numerical examples to assess the implication of their established measures. In the PF environment, a COPRAS method has also been proposed by them. Shen et al. [96] developed a new entropy for finding the weights of criteria in the VIKOR technique. However, despite the fact that it is one of the most vital tools in the fuzzy sets and Pythagorean fuzzy sets theories, the entropy measures for Pythagorean fuzzy sets are suggested within the perspective of the green supplier selection problem have remained limited, with only a handful of scholars focusing on them. As a result, this study proposes an entropy measure for Pythagorean fuzzy sets that is unique.

The following is a definition of the entropy measurement:

Definition 5. *An entropy* $e : PFS(X) \rightarrow [0,1]$ *estimate is a model that meets the following axioms:*

$$0 \leq e(U) \leq 1;$$

$e(U) = 0$ *if and only if U is a crisp set;*
$e(U) = 1$ *if and only if* $t_U(x_l) = f_U(x_l), \forall x_l \in X;$

$$e(U) = e(U^c);$$

For each $x_i \in X, e(U) \leq e(E)$ *if U is less than E, i.e.,* $t_U(x_l) \leq t_E(x_l) \leq f_E(x_l) \leq f_U(x_l)$ *or* $f_U(x_l) \leq f_E(x_l) \leq t_E(x_l) \leq t_U(x_l)$.

Theorem 1. *Let* U $\in PFS(X)$. *the entropy method can be defined as:*

$$e(U) = \frac{-1}{t(exp(2)-1)} \sum_{l=1}^{t} [\left(t_U^2(x_l) - f_U^2(x_l) \right) \left\{ exp\left(\frac{2t_U^2(x_l)}{t_U^2(x_l) + f_U^2(x_l)} \right) - exp\left(\frac{2f_U^2(x_l)}{t_U^2(x_l) + f_U^2(x_l)} \right) \right\} - exp(2) + 1]$$

3.3. Pythagorean Fuzzy Entropy SWARA COPRAS Method

We apply PF entropy SWARA COPRAS method to solve GSS problem with Pythagorean fuzzy knowledge. The weight is determined by mathematical calculation using an objective weighting model that does not consider expert preferences. The main property of the weight is to determine the relative importance of each factor or indicator and tends to share indicators. However, in the MCDM process, decision makers or experts often need to measure the subjective weight of standard judgments and opinions. Therefore, in this study, standard weights are evaluated based on objective and subjective weighting models by using Pythagorean fuzzy entropy and SWARA methods and overcome the shortcomings of subjective and objective weighting models. The ability of objective and subjective methods is combined in this comprehensive approach.

SWARA method is a common weight-assignment method in multi-criteria decision making. Compared with other methods, SWARA method is more concise in weight calculation and can more accurately obtain weight standards. In the implementation of SWARA method, first determine the interaction value of the criteria, as shown in Formula (1).

$$K = S_j + 1, \quad \forall j = (2, \ldots, n) \tag{1}$$

In Formula (1), S represents the relative weight value of the determination criteria, $\forall$ represents the symbol of discrete mathematics, and n represents the number of all criteria. The final weight value of the criterion is determined in Formula (2).

$$P = \frac{p_j}{\sum_{j=1}^{n} p_j}, \quad \forall j = (1, 2, \ldots, n) \tag{2}$$

In Formula (2), p_j represents the weight value calculated by the criterion. The process of determining weight value by SWARA method is shown in Figure 1.

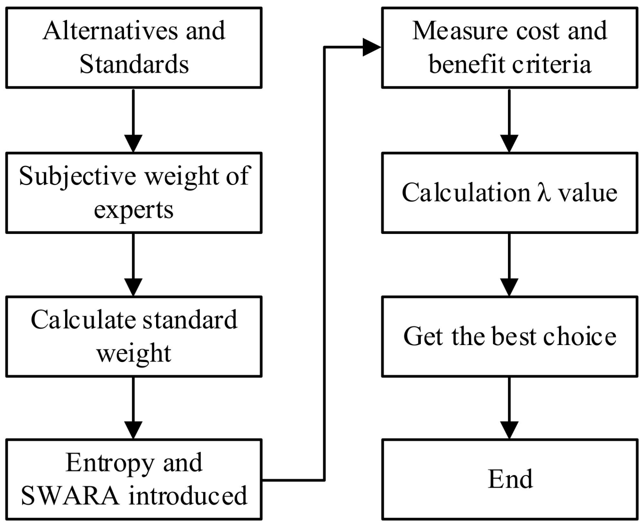

Figure 1. Process of weight value determination.

First. Step 1: Create an alternative and a set of criteria.

In a Pythagorean fuzzy set environment, a team of experts $\{M_1, M_2, \ldots, M_r\}$ indicate the desirable alternative for an MCDM process among a set of alternatives $\{B_1, B_2, \ldots, B_m\}$ under the set of criteria $\{G_1, G_2, \ldots, G_n\}$. Consider that each expert $M_k (k = 1, 2, \ldots, R)$ analyzes information in the form of a fuzzy Pythagorean decision matrix $\Upsilon^{(k)} = \left(x_{ij}\right)_{m \times n}$.

Second. Step 2: Assessment of weights based on the expert decision.

Let Pythagorean fuzzy number $\Gamma_k = (t_k, f_k, \pi_k)$. The kth expert's weight is now calculated as follows:

$$\omega_k = \frac{t_k^2\left(2 - t_k^2 - f_k^2\right)}{\sum_{k=1}^{r}\left[t_k^2\left(2 - t_k^2 - f_k^2\right)\right]} \tag{3}$$

where $\omega_k \geq 0$ and $\sum\limits_{k=1}^{r} \omega_k = 1$.

Third. Step 3: Criteria weights for decision matrices.

The individual decision-making viewpoints must be combined to form a collective viewpoint. We applied PF-weighted averaging (PFWA) method to create an aggregated PF-decision matrix.

$$z_{ij} = PFWA\left(y_{ij}^{(1)}, y_{ij}^{(2)}, \ldots, y_{ij}^{(r)}\right) = \left(\sqrt{1 - \prod_{k=1}^{r}\left(1 - t_k^2\right)^{\omega_k}}, \prod_{k=1}^{r}(f_k)^{\omega_k}\right) \quad (4)$$

where $Z = (z_{ij})_{m \times n}$

Fourth. Step 4: Criteria weights calculation through entropy and SWARA method.

In general, all of the criteria are not equally important. We assume the weight ($W = (w_1, w_2, \ldots, w_n)^T$) vector of the criterion set, that satisfies $\sum_{j=1}^{n} w_j = 1$ and $w_j \in [0, 1]$.

The procedure for evaluating W is as follows:

Objective weigh tw_j^o by entropy method.

We derive the objective weight w_j^o with the help of the formula below:

$$w_j^o = \frac{1 - \sum_{i=1}^{m}\left(h\left(z_{ij}\right)\right)}{n - \sum_{j=1}^{n}\sum_{i=1}^{m}\left(h\left(z_{ij}\right)\right)} \quad (5)$$

where $h(z_{ij})$ is the PFN z_{ij} entropy measure

SWARA method for Subjective weight w_j^s.

The SWARA model for weighting starts by ranking the criteria, then compares the criteria with lower-ranking criteria to the upper-ranking criteria.

The steps that explain how SWARA calculates the criteria weights are listed below:

A. Calculation of the score values:

Definition 3 is used to calculate the score values $S^*\left(z_{kj}\right)$ of PFNs.

B. Criteria Ranking.

According to the expert's opinion, each criterion is ranked from most- to least-important elements.

C. Calculate the average value's relative importance.

The criteria in the second position are used to determine their relative importance. The criteria are compared at the jth and (j − 1)th positions, the following comparative importance is determined.

D. Estimation of comparative coefficient.

The comparative coefficient c_j is measured as follows:

$$c_j = \begin{cases} 1, \ j = 1 \\ s_j + 1, \ j > 1 \end{cases} \quad (6)$$

where, s_j reflects the relative significance of average value in this case.

E. Weights calculation.

The new weight p_j is calculated as follows:

$$p_j = \begin{cases} 1, j = 1 \\ \frac{p_{j-1}}{c_j}, j > 1, j = 1, 2, \ldots, n \end{cases} \quad (7)$$

F. In this step the scaled weight is calculated as follows:

$$w_j^s = \frac{p_j}{\sum_{j=1}^{n} p_j} \quad (8)$$

Use Equations (6)–(9) to calculate the combined weights.

$$w_j = \theta w_j^o + (1 - \theta) w_j^s \quad (9)$$

where θ is the decision procedure's aggregating coefficient, which is between 0 and 1.

Fifth. Step 5: We measured the sum of values for cost and benefit type criteria.

Moreover, each option is distinguished by the addition of a benefit-maximizing criterion and a cost-reducing criterion Equations (11) and (12) are implemented to find the value of $\aleph_i$ as follows:

$$\aleph_i = \sum_{j=1}^{p} w_j z_{ij}, i = 1, 2, \ldots, m, \tag{10}$$

$$\pi_i = \sum_{j=p+1}^{n} w_j z_{ij}, i = 1, 2, \ldots, m, \tag{11}$$

where n and p represent the number of total criteria and benefit type.

Sixth. Step 6: The value of λ_i of ith option can be calculated as follows:

$$\beta_i = S^*(\sigma_i) + \frac{\min_i S^*(\pi_i) \sum_{i=1}^{m} S^*(\pi_i)}{S^*(\pi_i) \sum_{i=1}^{m} \frac{\min_i S^*(\pi_i)}{S^*(\pi_i)}} \tag{12}$$

where $\mathbb{S}^*(\sigma_i)$ and $\mathbb{S}^*(\varsigma_i)$ to represent the score values of σ_i and ς_i respectively.

Seventh. Step 7: The relative values of available options are used to specify the options for the priority degree in this method.

The option with the highest relative value is ranked as "higher priority," indicating the best choice.

$$\beta_{max} = \max_i \beta_i \tag{13}$$

Eighth. Step 8: The following is the formula for calculating each option degree of utility:

$$\vartheta_i = \frac{\beta_i}{\beta_{max}} \times 100\% \tag{14}$$

Equations (12) and (13) are used to express β_i and β_{max}, respectively. The developed COPRAS method can be used to determine the optimal solution from a group of alternatives using the interaction of multiple standards. The criteria and weights determined by the proposed method can be widely applied to the multi-criteria decision of sustainable green supplier selection in the era of Industry 4.0, and will not be affected by the case.

4. Results and Discussion

4.1. Case Study

Parallel to the advancement of information technologies, production systems have advanced to new levels. Organizations have changed their primary skills, improved their present environment, and developed the latest business techniques for their stakeholders and themselves as a result of global competition. The managers of an agri-based manufacturing industry in China demonstrate the application of the proposed GSS approach in this section. The manager's goal is to figure out how well suppliers are performing by looking at the application of the GSS criteria from the Industry 4.0 window. The organization that primarily manufactures lawnmowers maintains to expand its product line with no negotiating its quality measures and constant improvement, and it wishes to apply its ecological strategy throughout the supply chain, including cooperation actions with all suppliers in accordance with Industry 4.0 practices. GSS has been identified as a necessary decision-making activity for the XYZ company in light of this situation.

In light of Industry 4.0 components, XYZ wants to select the best green supplier. The supplier evaluation was conducted by a group of four decisionmakers, two men and two women, with an average age of 55.47. All members of the group had more than 15 years of decision-making experience. Face-to-face interviews were used to collect data. Four managers denoted by the letters DM1, DM2, DM3, and DM4, from the case company were chosen for the criteria ranking based on their direct involvement in similar decisions and decision-making processes. Each of the three experts has more than 15 years of experience. They were asked to conduct a pairwise comparison of the finalized criteria. It has been decided that the required part can be procured from one of five suppliers (S1, S2, S3, S4, S5).

4.2. The Evaluation of Alternative and Criteria

The literature review, academics, and expert opinions on CE-based Industry 4.0 for green supplier selection within company XYZ were used to identify the involved criteria. Twenty-one criteria were identified after a thorough review of the literature. The relevant literature was used to generate a list of initial factors. The stakeholders were then given those that were potentially influential in order to estimate the parameters that were expected to have an impact on the supplier selection domain. On a scale of 1–5, they were asked to rate the criteria's relevance. The scores were given a threshold based on their average. The elements that were above the threshold were chosen as the final evaluation criteria. Table 4 shows the final 16 sub-criteria, which are divided into four groups. With input from supply chain experts, these criteria were then categorized into four main categories for evaluation and ranking purposes. Table 5 contains the final list of items and their categorizations.

Table 4. Category of criteria of Industry 4.0 technology based on circular economy.

Dimension	Criteria	Reference
Economic dimensions (EC)	Product cost/price (ECO1)	(Dobos and Vörösmarty 2020) [97]
	Quality of production (ECO3)	(Gupta et al., 2019) [55]
	Efficient production methods (ECO4)	(Govindan et al., 2015b) [74]
	Access to finance and financial availability for implementing Industry 4.0 within circular economy (ECO5)	(Hasan et al., 2020) [59]
	Information technology (IT) facilities (ECO6)	(Ghadimi et al., 2019) [54]
Environmental dimensions (ENV)	Regular environmental audits (ENV1)	(Chen et al., 2020) [58]
	Green product design (ENV2)	(Banaeian et al., 2018) [57]
	Environmental competence (ENV3)	(Çalık 2021) [60]
	Presence of training facilities (ENV4)	(Kannan 2018) [98]
	Collaboration in environmental initiatives using Industry 4.0 technologies (ENV5)	(Schramm et al., 2020) [99]
	Readiness to apply Industry 4.0 in green initiatives (ENV6)	(Giannakis et al., 2020) [100]
	R&D in environmental issues using Industry 4.0 technologies (ENV7)	(Mubarik et al., 2021b) [76]
Social dimensions (SC)	Compliance with regulations (SOC1)	(Chen et al., 2020) [58]
	Information disclosure (SOC2)	(Banaeian et al., 2018) [57]
	Social responsibility (SOC3)	(Çalık 2021) [60]
	Work safety procedures (SOC4)	(Hasan et al., 2020) [59]

Table 5. Transformation rules of linguistic terms and Pythagorean fuzzy sets.

Linguistic Values	PFNs
Extremely Very important	(0.9000, 0.1500)
Very very important	(0.8000, 0.2500)
Very important	(0.7000, 0.4000)
Important	(0.6000, 0.4500)
Less important	(0.3500, 0.7000)
Very less important	(0.1500, 0.9500)

4.3. Criteria Weights USING ENTROPY and SWARA-COPRAS Method

After the study's criteria have been finalized, the next step is to calculate the criteria's weights using the PF-Entropy-SWARA-COPRAS approach [101,102]. Firstly, the differences between PF entropy SWARA COPRAS method and other methods are studied and compared [103,104]. The results are shown in Figure 2. Figure 2 shows that compared with the comparison algorithm, the method proposed in the study is closer to the subjective and objective evaluation values in weight calculation, so its standard weight calculation is more accurate.

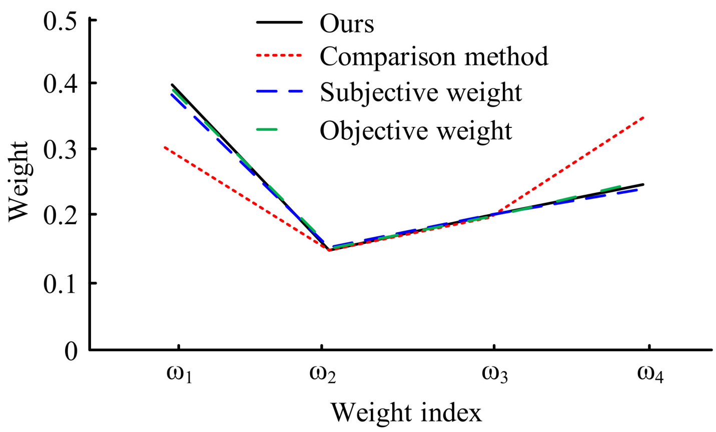

Figure 2. Index weight under different methods.

The case company's managers were given the task of selecting the best and worst criteria from the main category and subcategory criteria [105]. The decisionmaker's preference for a given standard and its weight are given a semantic evaluation to rearrange and evaluate the idea of GSS measures [106,107]. As a result, the evaluation weights based on the expert's opinion in terms of linguistic ratings are presented in Table 5. Moreover, the experts' weights for alternatives evaluation are presented in Table 6. The experts' weights for alternatives evaluation are measured using Table 5 and Equation (10). In addition, Table 7 shows the evaluations of the green supplier selection on each criterion based on experts' opinions. Based on decisionmaker opinion, Table 7 also shows the Pythagorean fuzzy decision matrix as a whole.

Table 6. Experts' weights for alternatives evaluation.

Experts	LVs	PFNs	Weights
DM1	Very very important	(0. 8000, 0.2500)	0.5205
DM2	Very important	(0. 7500, 0.3500)	0.4479
DM3	Important	(0. 6500, 0.4000)	0.3816

Table 7. The performance Evaluation of sustainable suppliers in terms of linguistic values.

Criteria	S1	S2	S3	S4	S5
ECO1	(MH, H, M)	(MH, ML, VL)	(VL, L, ML)	(MH, L, M)	(VH, M, L)
ECO2	(MH, L, H)	(L, ML, VL)	(H, L, ML)	(VH, VL, VVH)	(L, VH, MH)
ECO3	(H, MH, M)	(H, MH, ML)	(MH, H, VVH)	(L, H, VH)	(L, MH, VVH)
ECO4	(L, MH, VL)	(L, H, VH)	(H, ML, H)	(VH, VH, MH)	(VH, ML, L)
ECO5	(VH, L, ML)	(M, L, MH)	(VH, ML, L)	(H, VH, L)	(VH, L, ML)
ENV1	(H, MH, ML)	(L, MH, M)	(H, L, M)	(VL, VVH, H)	(H, VH, VL)
ENV2	(VVH, LH, H)	(VL, H, VH)	(H, ML, VH)	(VL, ML, H)	(VH, ML, MH)
ENV3	(M, H, ML)	(VH, H, M)	(H, L, ML)	(VVH, H, ML)	(L, ML, H)
ENV4	(M, L, ML)	(H, VH, MH)	(VH, M, ML)	(VVH, MH, ML)	(H, VH, VVH)
ENV5	(H, MH, ML)	(L, M, VL)	(H, VH, MH)	(L, H, MH)	(H, ML, L)
ENV6	(M, ML, VL)	(ML, L, H)	(H, MH, VH)	(VVH, ML, L)	(M, L, ML)
ENV7	(ML, VH, MH)	(H, L, ML)	(H, MH, VH)	(VH, ML, L)	(VH, H, VL)
SOC1	(H, L, ML)	(VH, MH, L)	(H, M, L)	(VH, ML, L)	(VH, VVH, MH)
SOC2	(M, VL, VVL)	(L, ML, VL)	(VH, H, ML)	(VH, H, L)	(H, VH, MH)
SOC3	(M, ML, L)	(H, ML, VH)	(VVH, L, M)	(H, L, ML)	(L, VL, VVL)
SOC4	(M, L, VL)	(MH, H, L)	(H, MH, VVH)	(M, VH, VVH)	(VL, L, ML)

The weights of the objective criteria for the applied entropy measure can be calculated using Table 8 and Equation (6) as follows:

$$w_j^o = (0.0519, 0.0512, 0.0480, 0.0507, 0.0364, 0.0537, 0.0569, 0.0591, 0.0523, 0.0541, 0.0516 \\ 0.0539, 0.0526, 0.0553, 0.0618, 0.0538)^T.$$

Table 8. Aggregated fuzzy Pythagorean decision matrix for green supplier selection.

Criteria	S1	S2	S3	S4	S5
ECO1	(0.620, 0.502, 0.603)	(0.597, 0.553, 0.582)	(0.733, 0.421, 0.534)	(0.847, 0.277, 0.453)	(0.687, 0.450, 0.571)
ECO2	(0.491, 0.634, 0.597)	(0.772, 0.380, 0.509)	(0.711, 0.444, 0.544)	(0.800, 0.350, 0.487)	(0.686, 0.456, 0.567)
ECO3	(0.321, 0.760, 0.565)	(0.377, 0.713, 0.591)	(0.521, 0.613, 0.594)	(0.585, 0.586, 0.560)	(0.234, 0.824, 0.516)
ECO4	(0.448, 0.610, 0.597)	(0.349, 0.747, 0.509)	(0.481, 0.660, 0.544)	(0.667, 0.494, 0.487)	(0.274, 0.816, 0.567)
ECO5	(0.200, 0.850, 0.487)	(0.337, 0.733, 0.591)	(0.620, 0.522, 0.586)	(0.875, 0.241, 0.421)	(0.326, 0.754, 0.570)
ENV1	(0.818, 0.320, 0.478)	(0.522, 0.616, 0.590)	(0.526, 0.612, 0.591)	(0.455, 0.682, 0.573)	(0.732, 0.422, 0.534)
ENV2	(0.637, 0.495, 0.591)	(0.466, 0.677, 0.570)	(0.308, 0.771, 0.558)	(0.525, 0.579, 0.624)	(0.604, 0.536, 0.590)
ENV3	(0.614, 0.562, 0.555)	(0.318, 0.758, 0.569)	(0.587, 0.572, 0.573)	(0.628, 0.549, 0.551)	(0.593, 0.567, 0.572)
ENV4	(0.515, 0.622, 0.591)	(0.319, 0.766, 0.558)	(0.289, 0.792, 0.538)	(0.638, 0.523, 0.565)	(0.587, 0.572, 0.573)
ENV5	(0.787, 0.354, 0.505)	(0.515, 0.622, 0.591)	(0.522, 0.616, 0.590)	(0.653, 0.508, 0.561)	(0.775, 0.369, 0.513)
ENV6	(0.297, 0.789, 0.539)	(0.269, 0.788, 0.554)	(0.587, 0.572, 0.573)	(0.593, 0.567, 0.572)	(0.604, 0.557, 0.570)
ENV7	(0.732, 0.422, 0.535)	(0.466, 0.677, 0.570)	(0.481, 0.660, 0.578)	(0.492, 0.638, 0.593)	(0.795, 0.344, 0.499)
SOC1	(0.579, 0.568, 0.585)	(0.300, 0.774, 0.557)	(0.658, 0.502, 0.561)	(0.702, 0.458, 0.545)	(0.769, 0.385, 0.510)
SOC2	(0.667, 0.494, 0.557)	(0.491, 0.634, 0.597)	(0.297, 0.789, 0.539)	(0.512, 0.637, 0.576)	(0.686, 0.475, 0.552)
SOC3	(0.484, 0.644, 0.593)	(0.492, 0.638, 0.593)	(0.515, 0.622, 0.591)	(0.653, 0.508, 0.561)	(0.638, 0.523, 0.565)
SOC4	(0.574, 0.572, 0.586)	(0.364, 0.720, 0.591)	(0.616, 0.534, 0.579)	(0.265, 0.789, 0.555)	(0.620, 0.502, 0.603)

Table 8 and Equation (5) are used to create aggregated Pythagorean fuzzy numbers based on the expert's opinions (Table 9). Definition 3 is also used to calculate the crisp values of corresponding aggregated Pythagorean fuzzy numbers.

Using the SWARA method to calculate the criteria weights, experts play a critical role in evaluating the previously conducted weights [108]. Each expert independently determined the size and scope of each factor. In the SWARA method, the most important criteria received the highest priority, while the least important criteria received the lowest [109,110]. The subjective weights of the criteria are highlighted in the last column of Table 10. The highest rankings in terms of expert judgments are for the range of access to finance and financial availability for implementing Industry 4.0 within the circular economy (ECO5) and R&D in environmental issues using Industry 4.0 technologies (ENV7), information technology (IT) facilities (ECO6) and product cost/price (ECO1).

Table 9. The decision maker's weighted criteria expressed as linguistic variables.

Sub-Criteria	Fuzzy Average Weights	Crisp Values
ECO1	0.728, 0.426, 0.537	0.7077
ECO2	0.484, 0.644, 0.593	0.4305
ECO3	0.709, 0.433, 0.557	0.6899
ECO4	0.644, 0.516, 0.576	0.6027
ECO5	0.723, 0.433, 0.539	0.7004
ENV1	0.308, 0.771, 0.558	0.2625
ENV2	0.477, 0.676, 0.562	0.4043
ENV3	0.465, 0.704, 0.537	0.3780
ENV4	0.739, 0.414, 0.532	0.7214
ENV5	0.340, 0.736, 0.586	0.3014
ENV6	0.659, 0.517, 0.546	0.6132
ENV7	0.559, 0.533, 0.635	0.5397
SOC1	0.545, 0.597, 0.588	0.4935
SOC2	0.272, 0.782, 0.561	0.2426
SOC3	0.507, 0.603, 0.616	0.4683
SOC4	0.781, 0.348, 0.519	0.7812

Table 10. The results of the SWARA approach for the criteria weight.

Criteria	Crisp Values	S_j	C_j	p_j	w_j
ECO5	0.8160	0.0669	0.8664	0.9776	0.0738
SOC2	0.7541	0.0629	0.9161	0.9247	0.0698
ECO6	0.7392	0.0140	0.8772	0.9128	0.0689
ECO1	0.7322	0.0080	0.8728	0.9068	0.0678
ENV4	0.7212	0.0110	0.8754	0.8978	0.0678
ENV7	0.6404	0.0798	0.9296	0.8370	0.0629
ENV2	0.6295	0.0110	0.8754	0.8279	0.0618
SOC4	0.6135	0.0170	0.8790	0.8160	0.0618
ENV3	0.5636	0.0499	0.9053	0.7811	0.0589
ECO4	0.5158	0.0479	0.9043	0.7481	0.0559
ENV6	0.4898	0.0259	0.8872	0.7302	0.0549
ENV5	0.4499	0.0399	0.8980	0.7053	0.0550
SOC1	0.4369	0.0130	0.8772	0.6963	0.0529
ECO3	0.4229	0.0140	0.8772	0.6873	0.0519
SOC3	0.3950	0.0279	0.8881	0.6714	0.0509
ENV1	0.3471	0.0479	0.9043	0.6424	0.0479

We use Equations (7)–(9) to measure each criteria subjective weights. The obtained subjective w_j^s weights are given below:

$$W_j^s = \begin{pmatrix} 0.089,\ 0.088,\ 0.087,\ 0.086,\ 0.081,\ 0.080,\ 0.079,\ 0.076,\ 0.074,\ 0.072,\ 0.069, \\ 0.068,\ 0.067,\ 0.064,\ 0.063,\ 0.061 \end{pmatrix}$$

Equation (8) can also be used to determine the combined weights:

$$W = \begin{pmatrix} 0.0730,\ 0.0707,\ 0.0686,\ 0.0698,\ 0.0620,\ 0.0689,\ 0.0700,\ 0.0710,\ 0.0660, \\ 0.0658,\ 0.0638,\ 0.0643,\ 0.0632,\ 0.0644,\ 0.0670,\ 0.0618 \end{pmatrix}^T$$

Further, we calculate the values of $\sigma_i, S^*(\sigma_i), \varsigma_i, S^*(\varsigma_i), \lambda_i$ and Ω_i. The preference order of green suppliers was rendered as $S_5 \succ S_1 \succ S_4 \succ S_3 \succ S_2$ in the last column of Table 11, indicating that S5 is the best supplier option. The optimal selection order was determined by alternative ranking; however, S5 and S1 received similar scores, while S4 received a significantly lower score. According to this analogy, the gap between S5 and S1 is smaller than the gap between S1 and S4. Furthermore, in terms of final ranking scores, the last two options (S3 and S2) are within a reasonable distance of the first three.

Table 11. Preference order of green suppliers' selection.

Alternatives	σ_i	$S^*(\sigma_i)$,	ς_i,	$S^*(\varsigma_i)$,	λ_i	Ω_i
S_1	(0.552, 0.619, 0.558)	0.438	(0.222, 0.921, 0.320)	0.101	0.635	92.713
S_2	(0.388, 0.741, 0.549)	0.286	(0.288, 0.896, 0.337)	0.14	0.428	62.506
S_3	(0.506, 0.657, 0.559)	0.391	(0.314, 0.882, 0.350)	0.16	0.516	75.307
S_4	(0.583, 0.595, 0.553)	0.468	(0.381, 0.847, 0.371)	0.214	0.561	81.957
S_5	(0.610, 0.568, 0.553)	0.499	(0.273, 0.902, 0.334)	0.131	0.651	95.000

4.4. Sensitivity Analysis

The results of the criterion weights are tested using a sensitivity analysis. We applied the fuzzy VIKOR technique to rank the suppliers. After obtaining the criteria weights, the next step is to rank a few selected suppliers based on these criteria's weights [111]. These three parameters are also calculated and shown in Table 12 and Figure 3, as well as in the results of the experiment. The suppliers are ranked based on their Q scores, which are given to them. The supplier with the lowest Q value is selected as the most suitable supplier for the job. Supplier 2 is ranked first because it has the lowest Q value and also meets both conditions, as well as the lowest R and S values, as shown in Table 12. Supplier 1 is ranked second because it has the lowest Q value and also meets both conditions, as shown in Table 12.

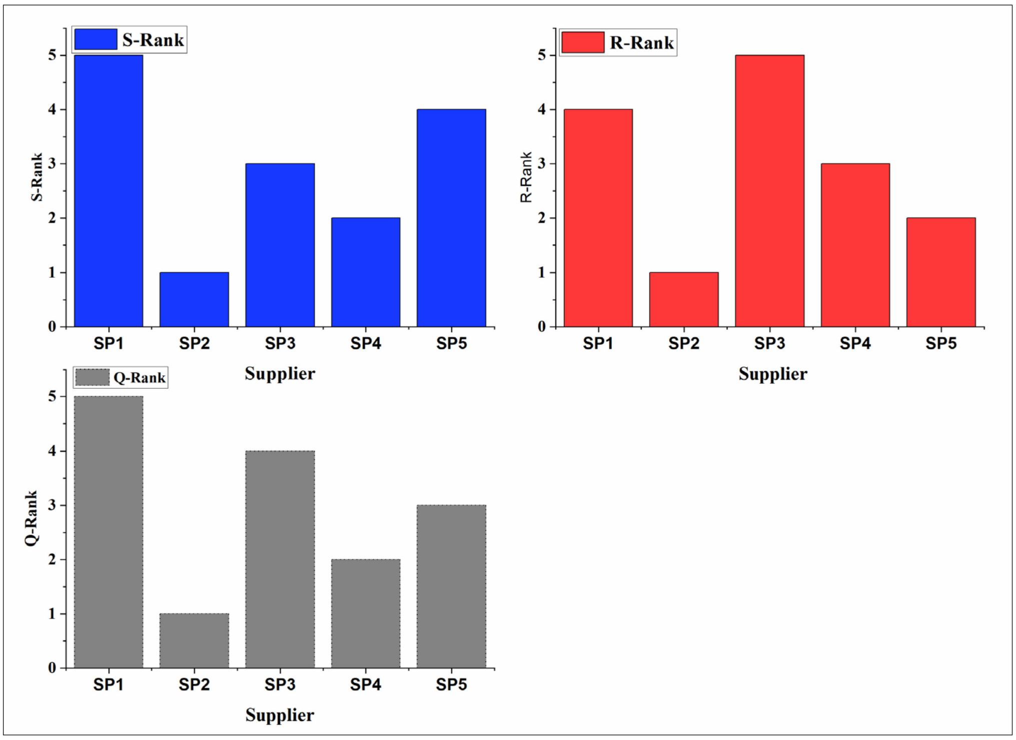

Figure 3. Alternatives for R, S, and Q values are ranked in order of preference.

Table 12. Ranking of alternatives for R, S, and Q values.

Supplier	R	Rank	S	Rank	Q	Rank
S5	0.1529	1	0.8915	1	0.9072	1
S1	0.1461	2	0.7308	2	0.7288	2
S4	0.1060	4	0.4211	3	0.6093	3
S3	0.1110	3	0.4169	4	0.4461	4
S2	0.0924	5	0.3569	5	0.3175	5

Finally, by studying and analyzing the impact of the proposed method on the multi criteria decision-making management of sustainable supplier selection, it can be seen that the enterprise decisionmakers can make the best decisions under the current standard and achieve sustainable development by the proposed multi-criteria decision-making method. In addition, under the influence of the multi-criteria decision-making method, the personal ability of managers can be continuously improved. When facing more uncontrollable factors, their ability in decision-making is more comprehensive.

5. Conclusions

Businesses must prioritize environmental competencies due to pressing climate change issues such as epidemics, global warming, and consumer and government demands. The introduction of new technologies such as Industry 4.0 technologies has resulted in changes in production and purchasing processes, as well as changes in the company's process of decisionmaking. This research aims to see how Industry 4.0 technology based on circular economy practices is incorporated into the green supplier selection problem. To find the best green supplier, a variety of methods are presented. PFSs have gained popularity in recent years as a useful tool for depicting the ambiguity of MCDM problems. PFSs can express ambiguity and uncertainty in decisionmakers' opinions, and they are better at dealing with the uncertainty of real-world problems. As a result, a new technique for GSS has been developed in this study, which takes into account Industry 4.0 technology applications using Pythagorean fuzzy information.

The case company's experts defined the evaluation criteria for the proposed approach, and the experts' assessments were based on Pythagorean fuzzy numbers' linguistic variables. The Pythagorean fuzzy entropy method was used to determine the objective weights of the evaluation criteria, and the subjective weights were determined using SWARA under uncertainty, which considers the similarity and the distance among the alternatives. The proposed decision-making framework was used to solve the green supplier selection problem, demonstrating the effectiveness of the proposed method. To determine the validity of the proposed procedure's outcome, sensitivity analysis and a comparison with the existing method were conducted to ensure that the proposed GSS approach was feasible.

The results of our case study show that three different criteria from the Industry 4.0 technology are the most important for GSS: production, delivery, and quality. These three criteria account for 88 percent of GSS's total weight. Decisionmakers want to expand their global presence by providing high-quality products. As a result, decisionmakers place the greatest emphasis on these criteria. According to the COPRAS results, the most important sub-criterion in the assessment was service level, Quality 4.0, IoT, and CPS criteria.

5.1. Policy Implications

Therefore, in order to improve production efficiency, the manufacturing process should be carried out with care and precision. Although quality techniques such as six sigma, kaizen, and just-in-time are important, the importance of standards has changed in the process of focusing on Industry 4.0 components. The digitalization of the supplier selection process is enabled by implementing key elements of Industry 4.0. While businesses face challenges in optimizing production processes, developing products, and utilizing product usage data. In this scenario, Industry 4.0 technology allows them to overcome these challenges. Data from product manufacturing processes and logistics operations aid in the improvement of services and products. All in all, to help management science professionals who act as decision mediators or even decision makers to make more effective and informed decisions concerning sustainable criteria and sustainable supplier performance that will ultimately lead to an overall improvement in the sustainability of the organization, this study provides an analytical framework and multi-criteria model.

5.2. Study Limitations and Future Direction

As a result of this research, the dimensions that companies wish to improve the supplier selection process in agricultural production enterprises should be taken into consideration are revealed through the Industry 4.0 window, which was used in this research. It was hoped that decisionmakers would be able to overcome uncertainty more easily as a result of the MCDM methods employed in the study. Different criteria that influence a buyer's decision-making process can be included in future studies, and the approach is broadened and applied to a variety of industries. Developing additional criteria for supplier selection and testing the framework in various other deve loping countries could be part of future research projects. However, social criteria are also important for sustainable supplier selection, and future studies can look into this aspect by looking at the results of the current study.

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