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Research article

Clustering sustainable suppliers in the plastics industry: A fuzzy equivalence relation approach

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ABSTRACT

Nowadays, pure economic supply chain management is not commonly contemplated among companies (especially buyers), as recently novel dimensions of supply chains, e.g., environmental, sustainability, and risk, play significant roles. In addition, since companies prefer buying their needs from a group of suppliers, the problem of supplier selection is not solely choosing or qualifying a supplier from among others. Buyers, hence, commonly assemble a portfolio of suppliers by looking at the multi-dimensional pre-determined selection criteria. Since sustainable supplier selection criteria are often assessed by linguistic terms, an appropriate clustering approach is required. This paper presents an innovative way to implement fuzzy equivalence relation to clustering sustainable suppliers through developing a comprehensive taxonomy of sustainable supplier selection criteria, including supply chain risk. Fifteen experts participated in this study to evaluate 20 suppliers and cluster them in the plastics industry. Findings reveal that the best partitioning occurs when the suppliers are divided into two clusters, with 4 (20%) and 16 (80%) suppliers, respectively. The four suppliers in cluster one are performing better in terms of the capability of supplier/delivery, service, risk, and sustainability criteria such as environment protection/management, and green innovation. These factors are critical in clustering and selecting sustainable suppliers. The originality of this study lies in developing an all-inclusive set of criteria for clustering sustainable suppliers and adding risk factors to the conventional supplier selection criteria. In addition to partitioning the suppliers and determining the best-performing ones, this study also highlights the most influential factors by analysing the suppliers in the best cluster.

1. Introduction

Globally, organisations are under enormous pressure to refine manufacturing, production, and consumption cycles to accommodate resource deficiencies and waste emissions. In this context, the emphasis on sustainability has been pronounced among both practitioners and scholars. They highlight companies' endeavours to factor in their economic, social, and environmental impacts. These considerations can result in waste reduction and the reintegration of resources into the production cycle. (Daoutidis et al., 2016; Genovese et al., 2017; Bai et al., 2022). Communities are increasingly scrutinizing the practices and programs of many firms with an emphasis on the development of sustainable industries. Social sustainability has grown from strength to strength within a firm and throughout the firm's eco-system, giving birth to sustainable supply chain management (SSCM) (Zarbakhshnia et al., 2020a; Fallahpour et al., 2021). SSCM is about using natural resources prudently, being aware of the environment, being socially responsible for employees' health and safety, and economic efficiency. Although SSCM can lend to comparative advantage, research in this province is scant (Tsai et al., 2021).

In a sustainable supply chain, firms expect their selected suppliers to fulfil environmental procedures like implementing waste reduction protocols, installing efficient mechanisms for controlling pollution, and substituting hazardous raw materials with non-hazardous ones (Xu et al., 2013). Accordingly, environmental factors play an important role in the supplier selection process (Mavi et al., 2013). The impacts of environmental protection on supplier selection decision-making along with exploring the effects of sustainable purchasing on waste reduction have been discussed (Handfield et al., 2002; Min and Galle, 1997). Research shows that waste reduction offers a range of benefits to a firm's

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environmental and financial performance (King and Lenox, 2001).

From a practical perspective, scholars have argued that various factors should be evaluated for managing firms' suppliers and making complex decisions in the supply chain (Yan et al., 2022). Supplier evaluation involves tangible and intangible factors (Abdel-Basset et al., 2019; Xing et al., 2022). Hosseini et al. (2022) report that all the members in the chain, from suppliers to managers, have to associate with sustainability to achieve a sustainable supply chain. The inability to design and produce sustainable products and processes implies that more waste will be fed to landfills. Thus, suppliers must acknowledge that the concept of zero-waste is part of a holistic approach to sustainability (Jain and Singh, 2020a; Zarbakhshnia et al., 2022).

Effective and appropriate supplier selection is of utmost importance for organisations. Sustainable supplier performance evaluation schemes can screen unqualified suppliers and are utilised to build a long-term collaboration with qualified ones. In practice, a sheer number of supplier combinations can be selected for partnership. Changing priorities of customers have compelled companies to cluster suppliers in terms of their competitive advantage, sustainability position, features of their products, and production strategies for effective supplier management and efficient alignment of products with customer demands (Che, 2012; Che and Wang, 2010; Ijadi Maghsoodi et al., 2018; Kuo et al., 2018). Companies apply clustering to reduce the complexity of identifying and selecting the most suitable suppliers for their needs (Heidarzade et al., 2016). As companies become more aware of their environmental impact, they increasingly seek ways to reduce waste and improve waste management practices. Supplier clustering enables companies to identify sustainable suppliers more easily to reduce their environmental impact, improve waste management practices, and achieve sustainability goals more effectively (Dimitrova et al., 2007; Jain and Singh, 2020; Nahaei et al., 2021). In addition, it enables companies to optimise their waste management processes by grouping suppliers based on their proximity to waste generation sites or to waste treatment and disposal facilities, to reduce waste transportation needs, thereby reducing associated emissions and costs. This helps companies cut their carbon footprint and other environmental impacts related to waste management (Ghose et al., 2006; Tirkolaee and Torkayesh, 2022). Therefore, in sustainable supplier selection, clustering suppliers helps companies avoid negative environmental and societal impacts and reduce reputational risks associated with unsustainable practices (Akman, 2015; Bracquené et al., 2021).

Supplier clustering poses a complex multi-criteria decision-making (MCDM) challenge (Coşkun et al., 2022). Since fuzzy equivalence relation effectively handles multiple criteria, our study extends this method by incorporating fuzzy analytic hierarchy process (FAHP) to accurately weigh criteria for clustering sustainable suppliers. Therefore, this paper provides two major contributions: (1) The research addresses the need for an all-inclusive set of criteria for clustering sustainable suppliers. By considering both sustainability and risk factors, the study recognises the importance of evaluating suppliers based on their environmental, social, and economic performance and ability to mitigate potential risks. This comprehensive approach enhances the effectiveness of supplier clustering processes. (2) The study acknowledges that not all criteria hold equal importance in supplier evaluation. The research extends fuzzy equivalence relations by incorporating the FAHP method to address this shortcoming. By determining the relative importance of different criteria using FAHP, this integrated approach enables a more nuanced and accurate supplier performance assessment, ensuring that critical criteria receive appropriate consideration during the clustering process. These contributions offer companies a robust framework to make informed decisions that align with sustainability objectives and mitigate potential risks across their supply chains.

The rest of the paper is organised as follows. Section 2 reviews the sustainable supplier selection and clustering literature. Section 3 presents the research methodology and develops a framework for clustering suppliers using fuzzy equivalence relations. Section 4 contains a case study and discusses the findings. Finally, Section 5 concludes the paper and provides future research directions. The Supplementary Materials present an illustrative example to help readers understand the research methods easily.

2. Literature review

2.1. Sustainable supplier selection vs. clustering

Two strategies distinguish SSCM: supplier management for risk and efficiency; and supply chain management of sustainable products. The first strategy involves mitigating a firm's potential loss of reputation due to poor sustainability. This calls for including environmental and social criteria with the economically-based supplier evaluation. The second strategy tries to enhance the environmental and social efficiency of the products through life-cycle-based standards at the supply chain level (Zarbakhshnia et al., 2019; Zhang et al., 2022). Research suggests that firms can improve their economic capital by increasing resources such as investments and focusing on intangible resources such as research and development and firm culture toward sustainability (Tang and Yang, 2021).

Many firms are still attempting to include sustainability principles into their supply chain by looking for the best method (Kumar et al., 2021), beyond the traditional economic approaches in supplier selection. Supplier selection affects many parameters, like ensuring that standards of product manufacturing are met with minimum wastes as the prime importance (Beullens and Ghiami, 2022). To this end, the environmental/ecological and social aspects must be added to the traditional supplier selection criteria of quality, cost, delivery, and service to remain in the sustainable supply chain (Rajeev et al., 2019). Many studies have argued that selecting the right sustainable supplier impacts cost, waste reduction, and supply chain efficiency (Kannan et al., 2020). For instance, Beullens and Ghiami (2022) discussed how supplier selection as a waste reduction strategy can contribute to waste reduction purposes by reducing the deterioration or rejection rate (Beullens and Ghiami, 2022). Alavi et al. (2021) considered waste reduction an influential criterion for sustainable supplier selection. Both environmental and social elements must be considered the most important elements in a firm's supplier selection game plan (Coşkun et al., 2022). With the increasing significance of sustainability in the marketplace, several aspects have become more important to the supplier selection process from several theoretical lenses (Shang et al., 2022). In their studies, Bai et al. (2022) identified a set of metrics for circular and sustainable supplier selection. Several empirical and conceptual works in their literature review indicate waste reduction and relevant criteria.

Using stakeholder theory, suppliers, employees, society, customers, and channel partners can present separate social problems in the supply chain (Memari et al., 2019). Scholars have highlighted the importance of human rights and labour conditions in the supply chain, emphasising health and safety, philanthropy, human rights, and ethics. However, they suggest that ethics is not a social dimension in the supply chain (Bai and Satir, 2022). Similarly, the resource dependency theory posits that external resources can affect the behaviour of a firm (Giri et al., 2022). As a result, firms have focused on efficiently managing supply chain operations to improve firms performance.

Sustainable supplier selection is needed to ensure a firm's survival, profitability, and success (Afrasiabi et al., 2022). The literature is replete with studies on sustainable supplier selection. For instance, Pamucar et al. (2022) developed a methodology to investigate supplier selection problems in various supply chain applications such as waste management. Zarbakhshnia and Jaghdani (2018) provided a two-stage DEA model considering uncontrollable inputs and undesirable outputs in the plastic industry to rank sustainable suppliers. Memari et al. (2019) provided an intuitionistic fuzzy TOPSIS to evaluate sustainable suppliers for a car parts manufacturer. Rashidi and Cullinane (2019) presented a comparison of fuzzy DEA and fuzzy TOPSIS in Swedish logistics service providers as suppliers to show the applicability of each method. Stević et al. (2020) represented a novel MCDM technique entitled measurement of alternatives and ranking according to compromise solution (MARCOS). Their model tested a sustainable supplier selection problem in the private healthcare industry in Bosnia and Herzegovina. Chen et al. (2020a) proposed a hybrid rough-fuzzy TOPSIS-DEMATEL method for sustainable supplier evaluation. Rough-fuzzy numbers were applied to deal with the uncertainty and qualitative criteria of the vehicle transmission case study. Mina et al. (2021) provided a hybrid approach consisting of fuzzy AHP and fuzzy TOPSIS to select the best suppliers in a circular environment to obtain sustainability goals in a petrochemical company. Ishizaka et al. (2022) proposed a novel hybrid decision-making model considering BWM-GAIA to select sustainable suppliers in a closed-loop supply chain in the Pakistani pharma sector. Five suppliers' performance analysis found "on-time delivery" as the most influential criterion in sustainable supplier selection. Nasri et al. (2022) integrated fuzzy DEMATEL, ANP, and DEA methods for supplier selection in the petroleum industry and found only three qualified suppliers. Govindan et al. (2023) analysed strategies for sustainable supplier selection using a hybrid approach consisting of BWM and TODIM. They indicated that "quality" and "information disclosure" are the two most important criteria.

Sustainable supplier selection refers to identifying and selecting suppliers who meet certain sustainability criteria, such as environmental performance, social responsibility, and ethical standards (Yazdani et al., 2021). This process aims to ensure that the products or services procured from these suppliers are produced sustainably and align with the organisation's sustainability goals (Lo et al., 2021; Chai et al., 2023). The selection process typically involves evaluating potential suppliers based on sustainability-related criteria, such as environmental impact, labour practices, and supply chain management (Giri et al., 2022). In contrast, clustering refers to grouping similar entities—suppliers in this case—based on certain characteristics or attributes (Jain and Singh, 2020b). Clustering aims to identify patterns or segments within a larger dataset to inform decision-making (Wen et al., 2020). It is used in various contexts, such as market segmentation or supply chain optimisation (Seo and Lee, 2022; Ahmad et al., 2022; Keskin, 2022; Ellis et al., 2023). Sustainable supplier clustering aims to group suppliers based on their similarities or differences in sustainability criteria (Kuo et al., 2021). It creates more efficient and effective supply chains by identifying suppliers with similar capabilities or performance metrics (Barakat et al., 2023; Khaleie et al., 2012). The literature on clustering sustainable suppliers provides valuable insights into how organisations can use clustering techniques to improve sustainability performance and achieve sustainability goals (Vörösmarty and Dobos, 2020). Organisations gain multiple benefits by clustering sustainable suppliers, e.g., including improved supply chain transparency, reduced supply chain risks, improved supplier relationships, efficient and streamlined supply chains, enhanced supplier performance, and improved stakeholder engagement (Chen et al., 2020b; Tavana et al., 2020; Jamalnia et al., 2022). These benefits can help organisations achieve sustainability objectives and improve supply chain performance (Sharma et al., 2022).

2.2. Criteria for clustering sustainable suppliers

The increasing importance of sustainability in procurement and supply chain management has recently enhanced the literature on sustainable supplier clustering. Researchers have identified a range of criteria to cluster suppliers based on their sustainability performance. The criteria for sustainable supplier clustering are important for several reasons: (a) by using these criteria to cluster suppliers based on their sustainability performance, organisations ensure that their procurement decisions align with their sustainability goals and objectives. This helps advance sustainability initiatives and promote responsible business practices (Izadikhah et al., 2021). (b) They help organisations assess supplier performance more accurately and identify improvement areas, resulting in better supplier management and more sustainable supply chains (Jain and Singh, 2020b). (c) Organisations can reduce the risk of environmental, social, and governance issues in their supply chains, mitigating reputational risks and improving stakeholder trust (Jamalnia et al., 2022). (d) Clustering can encourage suppliers to improve their performance and engage in sustainability initiatives resulting in more collaborative and productive relationships between organisations and their suppliers (Coşkun et al., 2022). (e) Clustering suppliers based on sustainability criteria promotes innovation in sustainable business practices and encourages suppliers to develop new solutions to sustainability challenges (Tavana et al., 2020). By using sustainability criteria to identify and manage suppliers, organisations can improve their sustainability performance and positively impact the environment, society, risk assessment, and the economy (Mavi and Mavi, 2019; Peppel et al., 2022). Table 1 summarises the common criteria used to evaluate, cluster, and select sustainable suppliers.

Quality: Quality control and assurance are two sides of quality. Quality assurance fulfils customer expectations for optimising the use of resources (Govindan et al., 2020). This is achieved using performance criteria, certifications, and awards. Total Quality Management (TQM), ISO 9000, EN 29000 and BS 5750 are examples of these performance certifications (Stević et al., 2020). Insurance theory assumes that the users are more risk-averse than the sellers and considers warranties as compensation paid to the users in case of a product deficiency (Chen et al., 2012; Fallahpour et al., 2021).

Costs: Cost is an important element in deciding on supplier selection. Choosing the right supplier decreases the cost. Costs contain logistics cost, product cost, purchasing price, and price performance value. Costs can extend to several subdivisions (Kaya and Yet, 2019; Shang et al., 2022).

The capability of Supplier/Delivery: Order fulfilment at the right time, right place with the right services to meet customer needs is a competitive advantage in today's customer-centric marketplace (Wisner et al., 2014). Lu et al. (2019) noted that successful order fulfilment relies on marrying the factors of order fulfilment capability, i.e., supply capability, technology capability, product development capability, lead time, the capability of research and design, and supply flexibility (Giri et al., 2022).

Services: In today's competitive business environment, firms must satisfy customers with high-quality but low-price products. The rate of delivering products on time needs a few numbers of demands that the supply chain can provide them in a pre-determined level of the processing order form (Foroozesh et al., 2018; Coşkun et al., 2022).

Environment protection/Management: Environmental protection and progress in the environmental management system (EMS) help inform buyers of the negative effects of the production process on the environment. Many buyers expect their suppliers to apply EMS such as ISO 14001 (Bai et al., 2019a; Coşkun et al., 2022).

Pollution Control: Buyers want suppliers with the right behaviour towards pollution (Gurel et al., 2015). Management systems for air emissions, wastewater, and the capability to decrease pollution and pollution control initiatives help firms to manage pollution (Stević et al., 2020).

Green Product: While the traditional selection criteria (cost, flexibility, quality, lead time) are valid, the green product is a new criterion (Ortiz-Barrios et al., 2021). The use of more environmentally friendly materials protects the environment. Reusing, recycling and green certificates are also criteria for green packaging (Kumar et al., 2017; Stević et al., 2020).

Green Image: Green image pertains to the relationship between consumers and natural resources and the process of designing products with identified criteria about the type of materials, capability to change processes and products to have a lesser effect on natural resources and increase in the market share of green customers (Villanueva-Ponce et al., 2015; Giri et al., 2022).

Table 1
Sustainability and risk criteria on the sustainable supplier selection and clustering problem.

Dimensions	Main criteria	Sub-criteria	References
Economic	**Quality (C_1)**	**$C_{1.1}$**: Quality systems (ISO 9001)	Mavi et al. (2017), Zarbakhshnia et al. (2018), Memari et al. (2019), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Giri et al. (2022), Chai et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{1.2}$: Quality assurance	Luthra et al. (2017), Zarbakhshnia et al. (2018), Stević et al. (2020), Hadian et al. (2020), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Giri et al. (2022), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{1.3}$: Reject rate	Memari et al. (2019), Tong et al. (2022), Giri et al. (2022)
		$C_{1.4}$: Warranties	Stević et al. (2020), Fallahpour et al. (2021)
	Costs (C_2)	**$C_{2.1}$**: Product cost	Luthra et al. (2017), Mavi et al. (2017), Zarbakhshnia et al. (2018), Stević et al. (2020), Hadian et al. (2020), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Giri et al. (2022), Debnath et al. (2023), Chai et al. (2023), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{2.2}$: Purchasing price	Mavi et al. (2017), Memari et al. (2019), Stević et al. (2020), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Rasmussen et al. (2023)
		$C_{2.3}$: Price performance value	Memari et al. (2019), Hosseini et al. (2022)
		$C_{2.4}$: Logistics cost	Luthra et al. (2017), Mavi et al. (2017), Zarbakhshnia et al. (2018), Stević et al. (2020), Fallahpour et al. (2021), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Giri et al. (2022), Debnath et al. (2023), Rasmussen et al. (2023)
	The capability of Supplier/Delivery (C_3)	**$C_{3.1}$**: Supplying capability	Hosseini et al. (2022), Shang et al. (2022), Rasmussen et al. (2023)
		$C_{3.2}$: Technological capability	Luthra et al. (2017), Zarbakhshnia et al. (2018), Memari et al. (2019), Stević et al. (2020), Fallahpour et al. (2021), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Giri et al. (2022), Chai et al. (2023), Rasmussen et al. (2023)
		$C_{3.3}$: Capability of product development	Stević et al. (2020), Shang et al. (2022), Rasmussen et al. (2023)
		$C_{3.4}$: Lead time	Luthra et al. (2017), Mavi et al. (2017), Zarbakhshnia et al. (2018), Stević et al. (2020), Hadian et al. (2020), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Coşkun et al. (2022), Debnath et al. (2023), Chai et al. (2023), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{3.5}$: Capability of R & D	Zarbakhshnia et al. (2018), Memari et al. (2019), Stević et al. (2020), Shang et al. (2022), Rasmussen et al. (2023)
		$C_{3.6}$: Capability of design	Mavi et al. (2017), Hadian et al. (2020)
		$C_{3.7}$: Supplier flexibility	Luthra et al. (2017), Memari et al. (2019), Stević et al. (2020), Tong et al. (2022), Coşkun et al. (2022), Giri et al. (2022), Chai et al. (2023), Hajiaghaei-Keshteli et al. (2023)
	Services (C_4)	**$C_{4.1}$**: Rate of processing the order forms	Mavi et al. (2017), Hadian et al. (2020), Tong et al. (2022), Debnath et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{4.2}$: Rate of delivery in time	Mavi et al. (2017), Hadian et al. (2020), Hosseini et al. (2022), Coşkun et al. (2022), Chai et al. (2023), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)
Environmental	**Environment protection/ management (C_5)**	**$C_{5.1}$**: Environment protection certification	Fallahpour et al. (2021), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{5.2}$: Environment efficiency	Zarbakhshnia et al. (2018), Stević et al. (2020), Hosseini et al. (2022), Giri et al. (2022), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{5.3}$: Eco-design production	Mavi et al. (2017), Memari et al. (2019), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{5.4}$: Environmental protection policies and plans	Zarbakhshnia et al. (2018), Stević et al. (2020), Shang et al. (2022), Debnath et al. (2023)
	Pollution Control (C_6)	**$C_{6.1}$**: Air emissions	Stević et al. (2020), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Shang et al. (2022), Giri et al. (2022)
		$C_{6.2}$: Wastewater	Zarbakhshnia et al. (2018), Memari et al. (2019)
		$C_{6.3}$: Capability decrease the pollution	Stević et al. (2020), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Shang et al. (2022), Giri et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{6.4}$: Pollution control Initiatives	Stević et al. (2020), Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Shang et al. (2022), Giri et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{6.5}$: Disposal	Mavi et al. (2017), Zarbakhshnia et al. (2018)
	Green Product (C_7)	**$C_{7.1}$**: Recycle	Mavi et al. (2017), Zarbakhshnia et al. (2018), Debnath et al. (2023)
		$C_{7.2}$: Green packaging	Tong et al. (2022), Hosseini et al. (2022), Rasmussen et al. (2023)
		$C_{7.3}$: Green certifications	Zarbakhshnia et al. (2018), Memari et al. (2019), Stević et al. (2020)
		$C_{7.4}$: Green production	Memari et al. (2019), Tong et al. (2022), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{7.5}$: Reuse	Mavi et al. (2017), Fallahpour et al. (2021), Debnath et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{7.6}$: Re-manufacture	Mavi et al. (2017), Zarbakhshnia et al. (2018), Hajiaghaei-Keshteli et al. (2023)
	Green Image (C_8)	**$C_{8.1}$**: Relation between the type of materials used and natural resources	Fallahpour et al. (2021), Coşkun et al. (2022), Giri et al. (2022), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)

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Table 1 (*continued*)

Dimensions	Main criteria	Sub-criteria	References
		$C_{8.2}$: Capability to change process and product for lesser effect in the natural resources	Fallahpour et al. (2021), Coşkun et al. (2022), Giri et al. (2022), Rasmussen et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{8.3}$: Green customers' market share	Coşkun et al. (2022), Giri et al. (2022)
	Green Innovation (C_9)	**$C_{9.1}$**: Green technology capability	Tong et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{9.2}$: Green design	Mavi et al. (2017), Zarbakhshnia et al. (2018), Memari et al. (2019), Hosseini et al. (2022), Giri et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{9.3}$: Planning and processing green products	Fallahpour et al. (2021)
		$C_{9.4}$: Recycling product design	Zarbakhshnia et al. (2018)
		$C_{9.5}$: Renewable product design	Memari et al. (2019)
		$C_{9.6}$: Redesign of product	Mavi et al. (2017), Zarbakhshnia et al. (2018)
	Hazardous Substance Management (C_{10})	**$C_{10.1}$**: Management of hazardous substances	Zarbakhshnia et al. (2018), Tong et al. (2022), Shang et al. (2022), Rasmussen et al. (2023)
		$C_{10.2}$: Prevention of mixed materials	Tong et al. (2022), Shang et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{10.3}$: Warehouse management	Tong et al. (2022), Shang et al. (2022)
		$C_{10.4}$: Inventory of hazardous substances	Tong et al. (2022), Debnath et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{10.5}$: Restriction of hazardous substance	Tong et al. (2022), Hajiaghaei-Keshteli et al. (2023)
Social	**Social responsibility (C_{11})**	**$C_{11.1}$**: Health and safety	Mavi et al. (2017), Bai et al. (2019b), Stević et al. (2020), Fallahpour et al. (2021), Hosseini et al. (2022), Shang et al. (2022), Giri et al. (2022), Debnath et al. (2023), Chai et al. (2023)
		$C_{11.2}$: Education	Bai et al. (2019b), Debnath et al. (2023), Chai et al. (2023), Hajiaghaei-Keshteli et al. (2023)
		$C_{11.3}$: Flexible working arrangements	Mavi et al. (2017), Bai et al. (2019b), Fallahpour et al. (2021), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022)
		$C_{11.4}$: wage and working condition	Fallahpour et al. (2021), Hosseini et al. (2022), Coşkun et al. (2022), Shang et al. (2022)
		$C_{11.5}$: Employment stability	Mavi et al. (2017), Bai et al. (2019b), Stević et al. (2020), Giri et al. (2022)
		$C_{11.6}$: Philanthropy	Fallahpour et al. (2021), Tong et al. (2022)
		$C_{11.7}$: Gender ratio	Fallahpour et al. (2021), Tong et al. (2022), Hosseini et al. (2022), Shang et al. (2022)
		$C_{11.8}$: Labor equity and supplier stock management	Mavi et al. (2017), Fallahpour et al. (2021), Coşkun et al. (2022), Shang et al. (2022), Giri et al. (2022)
		$C_{11.9}$: Voice of Customer (VOC)	Mavi et al. (2017), Bai et al. (2019b), Tong et al. (2022), Shang et al. (2022), Giri et al. (2022), Chai et al. (2023)
		$C_{11.10}$: Respect for the policy	Mavi et al. (2017), Fallahpour et al. (2021), Coşkun et al. (2022), Hajiaghaei-Keshteli et al. (2023)
		$C_{11.11}$: Reputation	Stević et al. (2020), Tong et al. (2022), Shang et al. (2022), Rasmussen et al. (2023)
Risk	Risk (**C_{12}**)	**$C_{12.1}$**: Operational risk	Chen and Zou (2017), Mavi et al. (2017), Vahidi et al. (2018), Zarbakhshnia et al. (2020b), Shang et al. (2022), Rasmussen et al. (2023)
		$C_{12.2}$: Organisational risk	Mavi et al. (2017), Zarbakhshnia et al. (2020b), Rasmussen et al. (2023)
		$C_{12.3}$: Financial risk	Mavi et al. (2017), Zarbakhshnia et al. (2020b), Tong et al. (2022), Rasmussen et al. (2023)

Green Innovation: Given the growing concern about the destruction of natural resources and environmental pollution, green innovation has received much notice recently, albeit the impact of green innovation on sustainable performance is poorly understood (Memari et al., 2019). Green technology capability, green design, planning and process, and green production are important criteria for green innovation.

Hazardous Substance Management: Given the un-harmonised regulations on dangerous goods management, supplier selection in SSCM is essential to manage procurements (Zarbakhshnia et al., 2018; Giri et al., 2022). The sub-criteria for hazardous substance management include the prevention of mixed material, warehouse management, and inventory management and control of hazardous substances.

Social: Social sustainability focuses on the issues of social justice and human rights, namely supplier human rights, labour conditions, codes of practice and social auditing, compliance with child labour laws, and social equity (gender, size, ethnicity, and conflict avoidance) through sourcing from different suppliers. Understanding the social aspects of network design decisions helps evaluate the supply chain's effect on its stakeholders (Eskandarpour et al., 2015; Bai et al., 2019b; Stević et al., 2020).

Risk: Risks can be external or internal to the supply chain. Dealing with risks proactively keeps a firm productive and dynamic (Mavi et al., 2017; Zarbakhshnia et al., 2020b; Shang et al., 2022). The risk criteria in this research are operational, organisational, and financial risks.

2.3. Clustering methods

Regardless of the approach, sustainable supplier clustering typically involves the following steps. (1) Define the organisation's goals through supplier clustering by identifying specific sustainability criteria and performance metrics to evaluate suppliers. (2) Collect and analyse data on supplier sustainability performance. Data might pertain to environmental impact, social responsibility, risk, and economic viability, among other factors. (3) Develop a clustering approach to group suppliers based on data analysis and the resulting sustainability performance. These models can use various techniques, including fuzzy logic and multi-criteria decision-making techniques. (4) Provide practical recommendations on supplier engagement, improvement plans, and targeted procurement strategies once the clusters are identified (Izadikhah et al., 2021).

A limited number of sustainable supplier clustering studies have addressed sustainable supplier clustering in recent years. Jain and Singh (2017) utilised the fuzzy Kano model for clustering suppliers based on only economic criteria for large-scale industries. Jain and Singh (2020a) clustered sustainable supplier selection criteria using the fuzzy Kano methodology. In their subsequent study, Jain and Singh (2020b) proposed a two-phase decision model that included the fuzzy Kano model for clustering sustainability criteria to identify essential criteria and a fuzzy inference system to analyse the sustainability performance index of all suppliers in an Indian iron and steel company. Izadikhah et al. (2021) initially employed a fuzzy screening system to identify and eliminate unqualified suppliers. Subsequently, they performed a data envelopment analysis to cluster suppliers. Baskir (2022) provided a type-2 fuzzy C-means algorithm for clustering sustainable suppliers in the automotive industry using linguistic sets.

2.3.1. Fuzzy equivalence relations

Fuzzy equivalence relation clustering stands out from other clustering approaches due to its unique characteristics (Liang et al., 2005; Wang, 2010; Wu and Liu, 2020). Unlike hard clustering methods like K-means, fuzzy equivalence relation enables soft or fuzzy clustering (Kumar and Srinivas, 2010; Pitchai et al., 2021). This flexibility allows data points to have partial membership in multiple clusters, accommodating the inherent uncertainty and ambiguity often present in real-world data (Chai, 2023). The fuzzy equivalence relation is particularly valuable in exploratory data analysis and situations where the number of clusters is unknown or subject to change (Beg and Rashid, 2017). It handles overlapping clusters and provides a nuanced representation of complex relationships within the data (Sfiris, 2021). Additionally, fuzzy equivalence relation offers computational efficiency and scalability advantages over hierarchical clustering, making it faster and more suitable for large datasets (Liu et al., 2019). Unlike density-based clustering algorithms like Density-based spatial clustering of applications with noise (DBSCAN), fuzzy equivalence relation takes a different approach to cluster observations (Ruspini et al., 2019). Instead of relying on density information, fuzzy equivalence relation focuses on fuzzy equivalence and gradual membership (Laohakiat and Sa-Ing, 2021). This allows for representing imprecise clusters and incorporating uncertainty in clustering (Grigorenko and Mihailovs, 2022). The choice of clustering algorithm should consider the specific characteristics and requirements of the dataset. Fuzzy equivalence relation clustering offers a flexible and adaptable approach that can handle uncertainty, overlapping clusters, and dynamic environments, making it a valuable tool in exploratory data analysis, knowledge discovery, and applications where a soft clustering paradigm is needed (Chandrawat et al., 2018; Wang et al., 2022).

3. An extension to fuzzy equivalence relations for cluster analysis

Fuzzy equivalence relations are commonly and efficiently used to assess the degree of similarity and connection between the members of a specific universe of discourse, and they are very successful in different applications, such as knowledge engineering, cluster analysis, and decision-making (Liu et al., 2019; Ciric et al., 2007; Medina et al., 2023). A clustering method can potentially assign certain data points to multiple clusters based on their characteristics. However, fuzzy clustering methods address this challenge by respecting the uncertainty and ambiguity of data (Kuo et al., 2018). The fuzzy equivalence relation method assumes that a system contains a set of criteria $C = (C_1, C_2, \ldots, C_n)$ which are the inputs for cluster analysis. A panel of experts possessing knowledge about the criteria, alternatives, and their impact on organisational objectives is vital in developing a clustering strategy for a firm. This study extends the fuzzy equivalence relation method by integrating fuzzy analytic hierarchy process for deriving the relative importance of evaluation criteria in clustering problems. Experts evaluate sustainable supplier clustering criteria using fuzzy analytic hierarchy process (steps 1–4), followed by the implementation of the fuzzy equivalence relation method (steps 5–9) to cluster the suppliers. The integrated framework is explained below:

Definition 1. The membership function, $\mu_{\tilde{A}}(X)$, of a triangular fuzzy number (TFN) $\tilde{A}$ which is a triplet (l, m, u) is as Eq. (1) (Lee, 2005):

$$\mu_{\tilde{A}}(X) = \begin{cases} \dfrac{x-l}{m-l}, l \le x \le m \\ \dfrac{u-x}{u-m}, m \le x \le u \\ 0, otherwise \end{cases} \tag{1}$$

Step 1Determine the decision goal: Identify the relevant criteria to evaluate the merits and demerits of each alternative to ensure that the goals are met. Developing the evaluation criteria is important to assess alternatives. It is necessary to form an expert group of size K to determine the relative importance of criteria and evaluate the performance of alternatives against those criteria to achieve the decision-making goal (Mavi et al., 2013).

Step 2. **Determine the weight of evaluation criteria. Fuzzy analytic hierarchy process (AHP) successfully derives the weights vector by conducting pa**irwise comparisons between criteria (Mavi and Standing, 2018). This approach is summarised below:

Step 2. a. Evaluate the importance of criteria in pairs to construct the fuzzy pairwise comparison decision matrix,$\tilde{D}^{(k)} = [\tilde{a}_{ij}{}^{(k)}]_{n\times n}$,$\tilde{a}_{ij}{}^{(k)} = (l_{ij}{}^{(k)}, m_{ij}{}^{(k)}, u_{ij}{}^{(k)})$ $\tilde{a}_{ij}{}^{(k)}$where represents the relative importance of criterion i against criterion j. These comparisons range from $\tilde{9}^{-1}$(absolutely less important) to $\tilde{9}$ (absolutely more important), (See Table 2 on p. 377 in (Mavi, 2014).

Step 2. b. Obtain theconsistency ratio (CR) of each decision matrix by replacing $\tilde{a}_{ij}{}^{(k)} = (l_{ij}{}^{(k)}, m_{ij}{}^{(k)}, u_{ij}{}^{(k)})$ with $m_{ij}{}^{(k)}$ (Mahmoudzadeh and Bafandeh, 2013). To achieve this, the consistency index (CI) and the principal eigenvalue of the decision matrix (λ_{max}) should be calculated using Eqs. (2) and (3) (Saaty, 1990). The ran dom index (RI) is a constant value depending on the dimensions of the decision matrix (see Alonso and Lamata (2006) for the scale).

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{2}$$

$$CR = \frac{CI}{RI} \tag{3}$$

If CR < 0.10, the decision matrix and the pairwise comparisons are consistent. Otherwise, the comparisons should be repeated.

Step 2. c. Determine the aggregated decision matrix using the geometric mean.

$$\tilde{D} = [\tilde{a}_{ij}]_{n\times n} : \tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \tag{4}$$

in which

$$l_{ij} = \left(\prod_{k=1}^{K} l_{ij}{}^{(k)}\right)^{1/n}, m_{ij} = \left(\prod_{k=1}^{K} m_{ij}{}^{(k)}\right)^{1/n}, u_{ij} = \left(\prod_{k=1}^{K} u_{ij}{}^{(k)}\right)^{1/n} \tag{5}$$

Step 2. d. Determine the priority weights using the modified Logarithmic Least Square method (Wang et al., 2006).

$$Min\ J = \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} \sum_{k=1}^{\delta_{ij}} \left[\left(\ln w_i^L - \ln w_j^U - \ln a_{ijk}^L\right)^2 + \left(\ln w_i^M - \ln w_j^M - \ln a_{ijk}^M\right)^2 + \left(\ln w_i^U - \ln w_j^L - \ln a_{ijk}^U\right)^2 \right]$$

$$w_i^L + \sum_{j=1, j\neq i}^{n} w_j^U \ge 1 \tag{6}$$

$$w_i^U + \sum_{j=1, j\neq i}^{n} w_j^L \le 1$$

$$\sum_{i=1}^{n} w_j^M = 1; i = 1, 2, \ldots, n$$

$$\sum_{i=1}^{n}\left(w_i^L + w_i^U\right) = 2$$

$$w_i^U \geq w_i^M \geq w_i^L > 0$$

The optimal solution of Program (6) shows the normalised fuzzy weight, $\widetilde{w}_i = (w_i^L, w_i^M, w_i^U)$, of each criterion.

Step 3. Generate the fuzzy decision matrix $\widetilde{A}^{(k)} = [\widetilde{a}_{ij}^{(k)}]_{m\times n}$; $\widetilde{a}_{ij}^{(k)} = (l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)})$ for performance evaluation. We measure the performance of each alternative in terms of the intended criteria. The comparison scale is designed to have seven levels of performance ranging from Very Low, VL=(0,0,0.2), through Low, L=(0,0.2,0.4), Between Low and Medium, BLM=(0.2,0.4,0.5), Medium, M=(0.4,0.5,0.6), Between Medium and High, BMH=(0.5,0.6,0.8), High, H=(0.6,0.8,1) to Very High, VH=(0.8, 1,1) performance (Wang, 2010). The decision matrix $\widetilde{A}^{(k)}$ is obtained through pairwise comparisons performed by expert k, in which $\widetilde{a}_{ij}^{(k)}$ denotes the performance of alternative $i\ (i = 1, 2, \ldots, m)$ against criterion $j\ (j = 1, 2, \ldots, n)$ given by expert k in achieving the decision goal.

Step 4Aggregate the fuzzy decision matrices. By doing step 3, we have k fuzzy decision matrices, $\widetilde{A}^{(k)}$, where $k = \{1, 2, \ldots, K\}$ is the number of experts. The average of all decision/assessment matrices is obtained by Eq. (7).

$$\widetilde{P} = \left[\frac{\widetilde{A}^{(1)} \oplus \widetilde{A}^{(2)} \oplus \ldots \oplus \widetilde{A}^{(k)}}{K}\right] \otimes \widetilde{W} \tag{7}$$

where $\widetilde{W} = [\widetilde{w}_{ij}]_{n\times n}$ is a diagonal matrix for which $\widetilde{w}_{ii} = (w_i^L, w_i^M, w_i^U)$ are the fuzzy weights of criteria obtained in Step 2.

Step 5. Assume that $\widetilde{X}_i = (X_{i1}, X_{i2}, \ldots, X_{in})$ is the i th sequence composed of n fuzzy numbers, where $i = 1, 2, \ldots, m$. Consider $\widetilde{P}$ as a data matrix consisting of m fuzzy sequences (Wang, 2010), i.e.,

$$\widetilde{P} = [X_{iq}]_{m\times n} \tag{8}$$

where i denotes sequences and q refers to fuzzy numbers.

Step 6. Having the data matrix $\widetilde{P}$, for any pair of fuzzy sequences, we can calculate the fuzzy binary relation as follows:

Let $X_{iq} = (x_{iql}, x_{iqm}, x_{iqu})$ be a triangular fuzzy number $i = 1, 2, \ldots, m$; $q = 1, 2, \ldots, n$. Define $T_q^+ = (t_{ql}^+, t_{qm}^+, t_{qu}^+)$ to indicate the upper limit, and $T_q^- = (t_{ql}^-, t_{qm}^-, t_{qu}^-)$ to indicate the lower limit of the q th fuzzy number of all sequences in data matrix $\widetilde{P}$ (Wang, 2010), where

$$t_{ql}^+ = \max_i\{x_{iql}\}, t_{qm}^+ = \max_i\{x_{iqm}\}, t_{qu}^+ = \max_i\{x_{iqu}\},$$

$$t_{ql}^- = \min_i\{x_{iql}\}, t_{qm}^- = \min_i\{x_{iqm}\}, t_{qu}^- = \min_i\{x_{iqu}\} \tag{9}$$

$i = 1, 2, \ldots, m; \quad q = 1, 2, \ldots, n.$

Step 7. Set $R = \{((i,j), \mu_R(i,j))\}$ as the binary relation between fuzzy sequences $\widetilde{X}_i$ and $\widetilde{X}_j$. The similarity and match of the two fuzzy data sequences are obtained by $\mu_R(i,j)$ which is the membership between the sequence $\widetilde{X}_i$ and sequence $\widetilde{X}_j$ (Wang, 2010).

$$\mu_R(i,j) = \left[\frac{1}{n}\sum_{q=1}^{n}\left(\frac{d\left(T_q^+, T_q^-\right) - \left|d\left(X_{iq}, X_{jq}\right)\right|}{d\left(T_q^+, T_q^-\right)}\right)\right]^2, \tag{10}$$

where

$$d\left(T_q^+, T_q^-\right) = \int_0^1\left(\left(T_q^+ - T_q^-\right)_\alpha^L + \left(T_q^+ - T_q^-\right)_\alpha^U\right)d\alpha = \frac{\left(t_{ql}^+ - t_{qu}^-\right) + 2\left(t_{qm}^+ - t_{qm}^-\right) + \left(t_{qu}^+ - t_{ql}^-\right)}{2} \tag{11}$$

and

$$d\left(X_{iq}, X_{jq}\right) = \int_0^1\left(\left(X_{iq}, X_{jq}\right)_\alpha^L + \left(X_{iq}, X_{jq}\right)_\alpha^U\right)d\alpha = \frac{\left(x_{iql} - x_{jqu}\right) + 2\left(x_{iqm} - x_{jqm}\right) + \left(x_{iqu} - x_{jql}\right)}{2} \tag{12}$$

Step 8The max-min transitive closure is implemented to ensure that R is reflexive, symmetric, fuzzy compatible relation, and fuzzy equivalence relation (Wang, 2010), where;

$$\mu_{R^2}(i,j) = max\min_k[\mu_R(i,k), \mu_R(k,j)],$$

$$\mu_{R^n}(i,j) = max\min_k[\mu_{R^{n-1}}(i,k), \mu_R(k,j)] \tag{13}$$

and

$$\mu_{R^*}(i,j) = \max_{k\geq 1}\mu_{R^k}(i,j), \forall i,j.$$

Combining all these memberships, R^* and R^n can be revised below: $\mu_{R^n}(i,j) \geq \mu_{R^*}(i,j)$; that is, $R^* \subseteq R^n$ obtained by definitions if $\mu_{R^n}(i,j) \geq max\min_k[\mu_{R^{n-1}}(i,k), \mu_R(k,j)], \forall i,j$. It is guaranteed that the sub-sets (clusters) do not overlap.

Step 9. Based on R and meeting transitive conditions, R^* is a fuzzy equivalence relation. To divide linguistic data sequences into partitions, a threshold value λ is needed, which is determined after obtaining R^*. Moreover, R^n can replace R^* for clustering.

Let R_λ^* be a binary relation on S and $R_\lambda = \{(x,y)|r(x,y) \geq \lambda, \forall x, y \in S\}$ where $0 \leq \lambda \leq 1$. Because $R^* = \{(i,j)|\mu_{R^*}(i,j) \geq \lambda\}$ and $0 \leq \lambda \leq 1$, the sequences should be partitioned following a unique rule: If $\mu_{R^*}(i,j) \geq \lambda$, sequences i and j are placed into the same cluster; otherwise, they are allocated to two separate clusters. When $\lambda = 1$ then R_λ^* typically divides m fuzzy data sequences into m separate clusters. To determine clusters for $0 \leq \lambda \leq 1$, a validation index (VI) is defined to decide on the appropriate value of λ. The highest validation index denotes the best clustering result (Wang, 2010).

$$VI = max\sum_{i=1}^{m}\sum_{j=1(i\neq j)}^{m}(\alpha(i,j) \times \mu_{R^*}(i,j) + (1 - \alpha(i,j)) \times (1 - \mu_{R^*}(i,j))), \tag{14}$$

Table 2
Aggregated fuzzy pairwise comparison matrix

$\widetilde{D}$	C1			C2			C3			C4			C5			C6		
	l_{i1}	m_{i1}	u_{i1}	l_{i2}	m_{i2}	u_{i2}	l_{i3}	m_{i3}	u_{i3}	l_{i4}	m_{i4}	u_{i4}	l_{i5}	m_{i5}	u_{i5}	l_{i6}	m_{i6}	u_{i6}
C1	1.000	1.000	1.000	1.000	1.260	1.442	0.111	0.111	0.111	0.121	0.138	0.160	0.188	0.232	0.303	6.000	7.000	8.000
C2	0.693	0.794	1.000	1.000	1.000	1.000	0.116	0.126	0.138	0.126	0.144	0.168	0.144	0.168	0.203	3.634	4.642	5.646
C3	9.000	9.000	9.000	7.230	7.958	8.653	1.000	1.000	1.000	1.000	1.000	1.000	2.621	3.634	4.642	7.612	8.320	9.000
C4	6.257	7.268	8.277	5.944	6.952	7.958	1.000	1.000	1.000	1.000	1.000	1.000	1.587	2.621	3.634	7.612	8.320	9.000
C5	3.302	4.309	5.313	4.932	5.944	6.952	0.215	0.275	0.382	0.275	0.382	0.630	1.000	1.000	1.000	7.230	7.958	8.653
C6	0.125	0.143	0.167	0.177	0.215	0.275	0.111	0.120	0.131	0.111	0.120	0.131	0.116	0.126	0.138	1.000	1.000	1.000
C7	0.200	0.250	0.333	0.303	0.437	0.794	0.116	0.131	0.150	0.120	0.131	0.146	0.120	0.137	0.158	2.289	3.302	4.309
C8	0.177	0.215	0.275	0.255	0.347	0.550	0.111	0.116	0.121	0.116	0.131	0.150	0.111	0.125	0.143	2.289	3.302	4.309
C9	3.000	4.000	5.000	3.634	4.642	5.646	0.116	0.126	0.138	0.188	0.232	0.303	0.275	0.382	0.630	6.082	6.868	7.612
C10	0.158	0.188	0.232	0.215	0.275	0.382	0.111	0.111	0.111	0.116	0.126	0.138	0.120	0.131	0.146	1.260	2.289	3.302
C11	2.080	3.175	4.217	2.289	3.302	4.309	0.143	0.167	0.200	0.144	0.168	0.203	0.188	0.232	0.303	5.130	6.000	6.804
C12	2.714	3.780	4.820	6.257	7.268	8.277	0.215	0.275	0.382	0.397	0.481	0.630	1.817	2.884	3.915	7.612	8.320	9.000
Fuzzy Weight	(w_1^L, w_1^M, w_1^U)			(w_2^L, w_2^M, w_2^U)			(w_3^L, w_3^M, w_3^U)			(w_4^L, w_4^M, w_4^U)			(w_5^L, w_5^M, w_5^U)			(w_6^L, w_6^M, w_6^U)		
	(0.038, 0.040, 0.063)			(0.029, 0.030, 0.039)			(0.226, 0.249, 0.265)			(0.189, 0.208, 0.221)			(0.107, 0.121, 0.141)			(0.007, 0.011, 0.012)		

$\widetilde{D}$	C7			C8			C9			C10			C11			C12		
	l_{i7}	m_{i7}	u_{i7}	l_{i8}	m_{i8}	u_{i8}	l_{i9}	m_{i9}	u_{i9}	l_{i10}	m_{i10}	u_{i10}	l_{i11}	m_{i11}	u_{i11}	l_{i12}	m_{i12}	u_{i12}
C1	3.000	4.000	5.000	3.634	4.642	5.646	0.200	0.250	0.333	4.309	5.313	6.316	0.237	0.315	0.481	0.207	0.265	0.368
C2	1.260	2.289	3.302	1.817	2.884	3.915	0.177	0.215	0.275	2.621	3.634	4.642	0.232	0.303	0.437	0.121	0.138	0.160
C3	6.649	7.652	8.653	8.277	8.653	9.000	7.230	7.958	8.653	9.000	9.000	9.000	5.000	6.000	7.000	2.621	3.634	4.642
C4	6.868	7.612	8.320	6.649	7.652	8.653	3.302	4.309	5.313	7.230	7.958	8.653	4.932	5.944	6.952	1.587	2.080	2.520
C5	6.316	7.319	8.320	7.000	8.000	9.000	1.587	2.621	3.634	6.868	7.612	8.320	3.302	4.309	5.313	0.255	0.347	0.550
C6	0.232	0.303	0.437	0.232	0.303	0.437	0.131	0.146	0.164	0.303	0.437	0.794	0.147	0.167	0.195	0.111	0.120	0.131
C7	1.000	1.000	1.000	1.000	2.000	3.000	0.168	0.203	0.255	2.289	3.302	4.309	0.177	0.215	0.275	0.111	0.125	0.143
C8	0.333	0.500	1.000	1.000	1.000	1.000	0.126	0.144	0.168	1.000	2.000	3.000	0.168	0.203	0.255	0.111	0.120	0.131
C9	3.915	4.932	5.944	5.944	6.952	7.958	1.000	1.000	1.000	5.518	6.542	7.560	1.000	2.000	3.000	0.232	0.303	0.437
C10	0.232	0.303	0.437	0.333	0.500	1.000	0.132	0.153	0.181	1.000	1.000	1.000	0.160	0.191	0.237	0.111	0.116	0.121
C11	3.634	4.642	5.646	3.915	4.932	5.944	0.333	0.500	1.000	4.217	5.241	6.257	1.000	1.000	1.000	0.188	0.232	0.303
C12	7.000	8.000	9.000	7.612	8.320	9.000	2.289	3.302	4.309	8.277	8.653	9.000	3.302	4.309	5.313	1.000	1.000	1.000
Fuzzy Weight	(w_7^L, w_7^M, w_7^U)			(w_8^L, w_8^M, w_8^U)			(w_9^L, w_9^M, w_9^U)			$(w_{10}^L, w_{10}^M, w_{10}^U)$			$(w_{11}^L, w_{11}^M, w_{11}^U)$			$(w_{12}^L, w_{12}^M, w_{12}^U)$		
	(0.010, 0.021, 0.029)			(0.008, 0.017, 0.019)			(0.054, 0.078, 0.091)			(0.008, 0.013, 0.021)			(0.042, 0.058, 0.067)			(0.143, 0.153, 0.170)		

Table 3
Linguistic ratings of 20 suppliers against 12 sustainability criteria.

$\tilde{P}$	C1			C2			C3			C4			C5			C6		
A1	0.7	0.9	1	0.65	0.85	1	0.7	0.9	1	0.75	0.95	1	0.7	0.9	1	0.68	0.85	0.95
A2	0.25	0.4	0.53	0.2	0.38	0.5	0.25	0.43	0.53	0.13	0.3	0.5	0.25	0.4	0.53	0.15	0.33	0.48
A3	0.2	0.38	0.5	0.35	0.48	0.58	0.25	0.4	0.53	0.28	0.43	0.58	0.23	0.4	0.55	0.28	0.43	0.58
A4	0.73	0.9	0.95	0.65	0.83	0.9	0.7	0.9	1	0.8	1	1	0.65	0.85	1	0.7	0.90	1
A5	0.33	0.48	0.6	0.2	0.38	0.5	0.28	0.43	0.58	0.28	0.43	0.58	0.28	0.45	0.58	0.3	0.48	0.63
A6	0.2	0.35	0.5	0.38	0.5	0.63	0.28	0.43	0.58	0.38	0.5	0.63	0.35	0.5	0.65	0.2	0.38	0.5
A7	0.28	0.43	0.58	0.15	0.33	0.48	0.35	0.5	0.65	0.28	0.45	0.58	0.28	0.43	0.58	0.4	0.50	0.6
A8	0.33	0.48	0.6	0.15	0.35	0.48	0.33	0.48	0.6	0.3	0.43	0.55	0.23	0.4	0.55	0.35	0.48	0.58
A9	0.75	0.95	1	0.68	0.85	0.95	0.7	0.9	1	0.75	0.95	1	0.75	0.95	1	0.8	1.00	1
A10	0	0.1	0.3	0	0.1	0.3	0	0.15	0.35	0	0.1	0.3	0	0.1	0.3	0	0.10	0.3
A11	0	0.1	0.3	0	0.2	0.4	0	0.05	0.25	0	0.2	0.4	0.05	0.15	0.33	0	0.10	0.3
A12	0.2	0.35	0.5	0.25	0.4	0.53	0.38	0.5	0.63	0.3	0.45	0.55	0.2	0.4	0.5	0.25	0.40	0.53
A13	0.2	0.35	0.5	0.33	0.45	0.6	0.2	0.4	0.5	0.3	0.45	0.55	0.33	0.48	0.6	0.2	0.38	0.5
A14	0.33	0.48	0.6	0.25	0.4	0.53	0.33	0.48	0.6	0.3	0.45	0.55	0.43	0.58	0.73	0.3	0.48	0.63
A15	0.25	0.4	0.53	0.25	0.45	0.6	0.23	0.4	0.55	0.25	0.4	0.53	0.3	0.45	0.55	0.35	0.48	0.65
A16	0.7	0.88	0.9	0.73	0.9	0.95	0.6	0.8	0.88	0.58	0.75	0.95	0.65	0.83	0.9	0.7	0.88	0.9
A17	0.33	0.48	0.6	0.25	0.43	0.53	0.23	0.4	0.55	0.28	0.43	0.58	0.2	0.35	0.5	0.2	0.40	0.5
A18	0.25	0.43	0.53	0.38	0.5	0.63	0.1	0.28	0.45	0.2	0.4	0.5	0.3	0.45	0.55	0.2	0.38	0.5
A19	0.1	0.3	0.45	0.35	0.48	0.58	0.28	0.43	0.58	0.45	0.55	0.7	0.4	0.53	0.68	0.4	0.5	0.6
A20	0	0.15	0.35	0.05	0.1	0.28	0	0.1	0.3	0	0.2	0.4	0	0.15	0.35	0	0.15	0.35

$\tilde{P}$	C7			C8			C9			C10			C11			C12		
A1	0.65	0.85	1	0.68	0.85	0.95	0.75	0.95	1	0.7	0.9	1	0.8	1	1	0.7	0.9	1
A2	0.28	0.43	0.58	0.2	0.38	0.5	0.15	0.35	0.48	0.2	0.38	0.5	0.3	0.45	0.55	0.1	0.3	0.45
A3	0.2	0.38	0.5	0.25	0.4	0.53	0.23	0.35	0.5	0.25	0.4	0.53	0.25	0.4	0.53	0.18	0.35	0.53
A4	0.68	0.85	0.95	0.65	0.85	1	0.68	0.85	0.95	0.75	0.95	1	0.8	1	1	0.65	0.85	1
A5	0.4	0.55	0.68	0.25	0.43	0.6	0.43	0.58	0.73	0.3	0.5	0.63	0.45	0.55	0.7	0.33	0.48	0.6
A6	0.25	0.43	0.53	0.2	0.38	0.5	0.35	0.5	0.65	0.33	0.45	0.6	0.23	0.38	0.55	0.25	0.4	0.53
A7	0.33	0.45	0.6	0.18	0.35	0.53	0.45	0.58	0.7	0.2	0.38	0.5	0.18	0.35	0.53	0.2	0.35	0.5
A8	0.15	0.33	0.48	0.25	0.43	0.53	0.25	0.43	0.53	0.25	0.43	0.53	0.2	0.35	0.5	0.3	0.43	0.55
A9	0.63	0.78	0.85	0.7	0.9	1	0.7	0.9	1	0.68	0.85	0.95	0.68	0.85	0.95	0.7	0.9	1
A10	0	0.05	0.25	0	0.1	0.3	0	0.05	0.25	0	0.1	0.3	0	0.2	0.4	0	0.1	0.3
A11	0	0.2	0.4	0.	0	0.2	0	0.1	0.3	0	0.1	0.3	0	0.05	0.25	0.05	0.1	0.28
A12	0.25	0.43	0.53	0.38	0.5	0.63	0.3	0.45	0.55	0.28	0.43	0.58	0.1	0.3	0.45	0.2	0.35	0.5
A13	0.33	0.48	0.6	0.3	0.45	0.63	0.25	0.43	0.53	0.43	0.53	0.65	0.33	0.45	0.6	0.28	0.45	0.58
A14	0.48	0.63	0.73	0.4	0.53	0.68	0.23	0.4	0.55	0.43	0.53	0.65	0.43	0.53	0.65	0.28	0.43	0.58
A15	0.25	0.4	0.53	0.2	0.35	0.5	0.25	0.4	0.53	0.33	0.48	0.6	0.2	0.4	0.5	0.25	0.4	0.53
A16	0.65	0.83	0.9	0.6	0.8	0.88	0.65	0.83	0.9	0.58	0.75	0.95	0.68	0.85	0.95	0.6	0.78	0.9
A17	0.35	0.48	0.58	0.2	0.35	0.5	0.25	0.4	0.53	0.1	0.3	0.45	0.1	0.3	0.45	0.38	0.5	0.63
A18	0.3	0.45	0.55	0.1	0.3	0.45	0.33	0.48	0.6	0.15	0.33	0.48	0.15	0.35	0.48	0.28	0.45	0.58
A19	0.28	0.45	0.58	0.43	0.55	0.73	0.28	0.43	0.58	0.3	0.45	0.55	0.25	0.4	0.53	0.28	0.43	0.58
A20	0	0.1	0.3	0	0.1	0.3	0	0.1	0.3	0	0.15	0.35	0	0.05	0.25	0.05	0.25	0.43

where

$$\alpha(i,j) = \begin{cases} 1, if\ i,j \in S \in P_{R^*_\lambda}, \\ 0, ifi \in S, j \in S, S, S \in P_{R^*_\lambda}\ and\ S \neq S. \end{cases} \quad (15)$$

4. Case study: results and discussion

The fuzzy equivalence relations clustering is implemented in the plastics industry as the case study. Fifteen subject matter experts with an academic background in supply chain management and at least five years of work experience in the plastics industry participated in this study. Participants evaluated and scored 20 suppliers against 60 sustainability evaluation sub-criteria.

4.1. Results

Table 2 shows the aggregated fuzzy pairwise comparison matrix for twelve categories of sustainable supplier clustering and selection criteria. The consistency ratio of all comparison matrices is less than 0.1, and that for the aggregated fuzzy pairwise comparison matrix is 0.091. The last row of Table 2 shows the weights of criteria obtained by Program (6). Results show that 'the capability of supplier/delivery', 'services' and 'risks' are the top three most important criteria. Overall, the order of criteria according to their importance is shown below:

$$C_3 \succ C_4 \succ C_{12} \succ C_5 \succ C_9 \succ C_{11} \succ C_1 \succ C_2 \succ C_7 \succ C_8 \succ C_{10} \succ C_6$$

As the aggregated decision matrix in Step 4 is dependent on the weights of criteria, changes in the weights might result in new clustering schemes.

Table 3 represents the weighted aggregated linguistic ratings of suppliers as the decision matrix, $\widetilde{P}$, obtained using Eq. (7). For simplicity and to reduce the complexity of calculations, scores of the suppliers on 60 sustainability sub-criteria are aggregated in the corresponding 12 major criteria using the arithmetic mean. In this study, we assumed that the sub-criteria of each criterion/dimension have the same weight.

The similarity of suppliers in terms of sustainability criteria is computed via the fuzzy equivalence relations. Following steps 5–9, the initial relation matrix of 20 sequences, which is a fuzzy compatible matrix (R^1), and the fuzzy equivalence matrix (R^*) are shown in Table 4. Since all the elements on the diagonal of the initial relation matrix are 1, it satisfies the symmetric condition. The initial relation matrix also meets the reflexive condition since it equals the transposed initial relation matrix.

Applying the fuzzy equivalence relation to the sustainable supplier clustering problem shows that there are 12 intervals for λ: [0, 0.37], (0.37, 0.54], (0.54, 0.81], (0.81, 0.84], (0.84, 0.85], (0.85, 0.86], (0.86, 0.87], (0.87, 0.88], (0.88, 0.9], (0.9, 0.91], (0.91, 0.93], and (0.93, 0.1]. A different set of sustainable suppliers lie in the clusters at each interval. The best cluster is the one that has the highest value of the validation index. Thus, interval #2, (0.37, 0.54], with a validation index of 291.66, gives the best clustering scheme of the sustainable suppliers. We have two clusters with 16 and 4 suppliers from this interval, respectively. Table 5 reveals that the panel of experts has given the suppliers A1, A4, A9, and A16 a higher score. Therefore, decision-makers in the plastics industry can establish contracts with these suppliers who have better performance metrics. Following the proposed structured decision-making process can help firms save significant money and time by knowing and working with the best suppliers instead of collaborating with inappropriate partners.

4.2. Discussion

Applying sustainability in supply chain management leads to

Table 4
Fuzzy compatible matrix (R^1) and fuzzy equivalence matrix (R^*) of 20 suppliers' preferences.

Fuzzy compatible matrix (R^1)

No.	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	1	0.13	0.16	0.93	0.24	0.20	0.19	0.17	0.90	0.00	0.01	0.17	0.20	0.27	0.18	0.81	0.16	0.15	0.23	0.01
A2	0.13	1	0.87	0.14	0.76	0.80	0.81	0.82	0.14	0.49	0.51	0.82	0.81	0.72	0.85	0.21	0.82	0.81	0.74	0.54
A3	0.16	0.87	1	0.17	0.78	0.87	0.83	0.88	0.16	0.45	0.46	0.88	0.86	0.75	0.91	0.24	0.84	0.83	0.82	0.49
A4	0.93	0.14	0.17	1	0.25	0.20	0.19	0.18	0.87	0.01	0.01	0.18	0.21	0.27	0.18	0.81	0.17	0.16	0.23	0.01
A5	0.24	0.76	0.78	0.25	1	0.79	0.83	0.83	0.25	0.33	0.34	0.77	0.83	0.86	0.82	0.34	0.79	0.75	0.77	0.36
A6	0.20	0.80	0.87	0.20	0.79	1	0.82	0.81	0.20	0.39	0.40	0.85	0.87	0.76	0.88	0.29	0.80	0.85	0.86	0.43
A7	0.19	0.81	0.83	0.19	0.83	0.82	1	0.87	0.19	0.40	0.41	0.85	0.77	0.75	0.85	0.28	0.81	0.81	0.77	0.44
A8	0.17	0.82	0.88	0.18	0.83	0.81	0.87	1	0.18	0.42	0.44	0.86	0.81	0.80	0.87	0.26	0.85	0.79	0.79	0.47
A9	0.90	0.14	0.16	0.87	0.25	0.20	0.19	0.18	1	0.00	0.01	0.17	0.21	0.27	0.18	0.80	0.16	0.16	0.23	0.01
A10	0.00	0.49	0.45	0.01	0.33	0.39	0.40	0.42	0.00	1	0.88	0.43	0.38	0.30	0.42	0.03	0.44	0.45	0.35	0.88
A11	0.01	0.51	0.46	0.01	0.34	0.40	0.41	0.44	0.01	0.88	1	0.44	0.39	0.31	0.43	0.03	0.46	0.47	0.36	0.90
A12	0.17	0.82	0.88	0.18	0.77	0.85	0.85	0.86	0.17	0.43	0.44	1	0.84	0.78	0.85	0.26	0.83	0.79	0.82	0.47
A13	0.20	0.81	0.86	0.21	0.83	0.87	0.77	0.81	0.21	0.38	0.39	0.84	1	0.84	0.87	0.29	0.82	0.82	0.85	0.42
A14	0.27	0.72	0.75	0.27	0.86	0.76	0.75	0.80	0.27	0.30	0.31	0.78	0.84	1	0.79	0.37	0.75	0.70	0.81	0.34
A15	0.18	0.85	0.91	0.18	0.82	0.88	0.85	0.87	0.18	0.42	0.43	0.85	0.87	0.79	1	0.26	0.84	0.85	0.84	0.46
A16	0.81	0.21	0.24	0.81	0.34	0.29	0.28	0.26	0.80	0.03	0.03	0.26	0.29	0.37	0.26	1	0.24	0.23	0.32	0.04
A17	0.16	0.82	0.84	0.17	0.79	0.80	0.81	0.85	0.16	0.44	0.46	0.83	0.82	0.75	0.84	0.24	1	0.85	0.74	0.49
A18	0.15	0.81	0.83	0.16	0.75	0.85	0.81	0.79	0.16	0.45	0.47	0.79	0.82	0.70	0.85	0.23	0.85	1	0.76	0.50
A19	0.23	0.74	0.82	0.23	0.77	0.86	0.77	0.79	0.23	0.35	0.36	0.82	0.85	0.81	0.84	0.32	0.74	0.76	1	0.39
A20	0.01	0.54	0.49	0.01	0.36	0.43	0.44	0.47	0.01	0.88	0.90	0.47	0.42	0.34	0.46	0.04	0.49	0.50	0.39	1

Fuzzy equivalence matrix (R^*)

No.	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	1	0.37	0.37	0.93	0.37	0.37	0.37	0.37	0.90	0.37	0.37	0.37	0.37	0.37	0.37	0.81	0.37	0.37	0.37	0.37
A2	0.37	1	0.87	0.37	0.84	0.87	0.87	0.87	0.37	0.54	0.54	0.87	0.87	0.84	0.87	0.37	0.85	0.85	0.86	0.54
A3	0.37	0.87	1	0.37	0.84	0.88	0.87	0.88	0.37	0.54	0.54	0.88	0.87	0.84	0.91	0.37	0.85	0.85	0.86	0.54
A4	0.93	0.37	0.37	1	0.37	0.37	0.37	0.37	0.90	0.37	0.37	0.37	0.37	0.37	0.37	0.81	0.37	0.37	0.37	0.37
A5	0.37	0.84	0.84	0.37	1	0.84	0.84	0.84	0.37	0.54	0.54	0.84	0.84	0.86	0.84	0.37	0.84	0.84	0.84	0.54
A6	0.37	0.87	0.88	0.37	0.84	1	0.87	0.88	0.37	0.54	0.54	0.88	0.87	0.84	0.88	0.37	0.85	0.85	0.86	0.54
A7	0.37	0.87	0.87	0.37	0.84	0.87	1	0.87	0.37	0.54	0.54	0.87	0.87	0.84	0.87	0.37	0.85	0.85	0.86	0.54
A8	0.37	0.87	0.88	0.37	0.84	0.88	0.87	1	0.37	0.54	0.54	0.88	0.87	0.84	0.88	0.37	0.85	0.85	0.86	0.54
A9	0.90	0.37	0.37	0.90	0.37	0.37	0.37	0.37	1	0.37	0.37	0.37	0.37	0.37	0.37	0.81	0.37	0.37	0.37	0.37
A10	0.37	0.54	0.54	0.37	0.54	0.54	0.54	0.54	0.37	1	0.88	0.54	0.54	0.54	0.54	0.37	0.54	0.54	0.54	0.88
A11	0.37	0.54	0.54	0.37	0.54	0.54	0.54	0.54	0.37	0.88	1	0.54	0.54	0.54	0.54	0.37	0.54	0.54	0.54	0.90
A12	0.37	0.87	0.88	0.37	0.84	0.88	0.87	0.88	0.37	0.54	0.54	1	0.87	0.84	0.88	0.37	0.85	0.85	0.86	0.54
A13	0.37	0.87	0.87	0.37	0.84	0.87	0.87	0.87	0.37	0.54	0.54	0.87	1	0.84	0.87	0.37	0.85	0.85	0.86	0.54
A14	0.37	0.84	0.84	0.37	0.86	0.84	0.84	0.84	0.37	0.54	0.54	0.84	0.84	1	0.84	0.37	0.84	0.84	0.84	0.54
A15	0.37	0.87	0.91	0.37	0.84	0.88	0.87	0.88	0.37	0.54	0.54	0.88	0.87	0.84	1	0.37	0.85	0.85	0.86	0.54
A16	0.81	0.37	0.37	0.81	0.37	0.37	0.37	0.37	0.81	0.37	0.37	0.37	0.37	0.37	0.37	1	0.37	0.37	0.37	0.37
A17	0.37	0.85	0.85	0.37	0.84	0.85	0.85	0.85	0.37	0.54	0.54	0.85	0.85	0.84	0.85	0.37	1	0.85	0.85	0.54
A18	0.37	0.85	0.85	0.37	0.84	0.85	0.85	0.85	0.37	0.54	0.54	0.85	0.85	0.84	0.85	0.37	0.85	1	0.85	0.54
A19	0.37	0.86	0.86	0.37	0.84	0.86	0.86	0.86	0.37	0.54	0.54	0.86	0.86	0.84	0.86	0.37	0.85	0.85	1	0.54
A20	0.37	0.54	0.54	0.37	0.54	0.54	0.54	0.54	0.37	0.88	0.90	0.54	0.54	0.54	0.54	0.37	0.54	0.54	0.54	1

Table 5
Partitioning of 20 suppliers' preferences for different intervals of λ_y.

Interval of λ_y	Number of clusters	Clustering arrangement	Validation index
[0, 0.37]	1	{A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,A12,A13,A14,A15,A16,A17,A18,A19,A20}	258.41
(0.37, 0.54]	2	{A1,A4,A9,A16}, {A2, A3,A5,A6,A7,A8,A10,A11,A12,A13,A14,A15,A17,A18,A19,A20}	291.66
(0.54, 0.81]	3	{A10,A11,A20},{A1,A4,A9,A16}, {A2, A3,A5,A6,A7,A8,A12,A13,A14,A15,A17,A18,A19}	286.11
(0.81, 0.84]	4	{A1,A4,A9},{A16}, {A10,A11,A20}, {A2,A3,A5,A6,A7,A8,A12,A13,A14,A15,A17,A18, A19}	282.37
(0.84, 0.85]	5	{A5,A14},{A16}, {A1,A4,A9}, {A10,A11,A20}, {A2,A3,A6,A7,A8,A12,A13,A15,A17,A18,A19}	252.63
(0.85, 0.86]	7	{A5,A14},{A16},{A17},{A18}, {A1,A4,A9}, {A10,A11,A20}, {A2,A3,A6,A7,A8,A12,A13,A15,A19}	226.13
(0.86, 0.87]	9	{A5},{A14},{A16,},{A17},{A18,},{A19}, {A1,A4,A9}, {A10,A11,A20}, {A2,A3,A6,A7,A8,A12,A13,A15}	213.1
(0.87, 0.88]	12	{A2},{A5},{A7},{A13},{A14,},{A17},{A18,},{A19}, {A1,A4,A9}, {A10,A11,A20}, {A3,A6,A8,A12,A15}	186.37
(0.88, 0.9]	16	{A2},{A5},{A6},{A7}{A8}{A10},{A12}, {A13}, {A14},{A16},{A17},{A18},{A19}, {A11,A20},{A3,A15}, {A1,A4,A9}	169.7
(0.9, 0.91]	18	{A2},{A5},{A6},{A7},{A8},{A9},{A10},{A11},{A12}, {A13},{A14},{A16},{A17},{A18},{A19},{A20}, {A1,A4},{A3,A15},	164.95
(0.91, 0.93]	19	{A2},{A3},{A5},{A6},{A7},{A8},{A9},{A10},{A11},{A12}, {A13},{A14},{A15},{A16},{A17},{A18},{A19},{A20}, {A1,A4}	163.31
(0.93, 1.0]	20	{A1},{A2},{A3},{A4},{A5},{A6},{A7},{A8}, {A9}, {A10}, {A11},{A12},{A13},{A14}, {A15},{A16},{A17},{A18}, {A19},{A20}	161.59

reducing negative influences in the operations of supply chains. It also manages the effectiveness of three pillars of sustainability simultaneously (Ecer and Pamucar, 2020). As societies and governments began pressing companies to consider sustainability in their supply chains, businesses are now notified about the benefits they can achieve by concentrating on three dimensions of sustainability in a supply chain. From an environmental and economic perspective, supplier selection affects many parameters, such as decreasing waste and material usage, thereby increasing financial benefits. Reducing waste in sustainable supplier selection can lead to economic benefits such as cost reduction (Doonan et al., 2005). There are novel improvisations in sustainable supply chain management that yield successful and sustainable results for firms by showing a roadmap to a win-win strategy. Therefore, companies are more likely to focus on sustainable development for this competitive advantage (Ahmadi et al., 2020). Implementing socially and environmentally sustainable business operations challenges companies in managing and maintaining profitability. Hence, they are encouraged to work on risk assessment programs in addition to sustainable development (Zimmer et al., 2016). Considering risk factors, therefore, is one of the key practices for each organisation. One of the crucial activities in this context is evaluating the collaboration of suppliers and assessing their contributions to a sustainable supply chain. In the presence of risk factors, sustainable supplier evaluation is beneficial for helping companies obtain sustainability aims (Mina et al., 2021). Consequently, they compile a portfolio of suppliers based on multi-dimensionally determined attributes. Since linguistic data sequences typically represent sustainable supplier attributes, this study employs an appropriate clustering approach.

This study uses a fuzzy equivalence relation approach to cluster a set of sustainable suppliers in the presence of risk criteria. Clustering scheme #2 at the interval (0.37, 0.54] with the validation index of 291.66, reveals the best clustering of sustainable suppliers. Given that suppliers 1, 4, 9, and 16 are the best, Table 5 shows their very high scores regarding the capability of supplier/delivery, services, environment protection/management, risk, and green innovation, respectively. This is inferred that these criteria are the most influential for selecting and screening sustainable suppliers. It also highlights that industry practitioners, managers, and academics acknowledge the importance and criticality of environmental issues besides economic and risk dimensions. However, social sustainability criteria are still suffering from low recognition. It is worth noting that risk has been considered one of the most important criteria for the selected cluster because it makes the chosen suppliers resilient in the face of disruptive events such as market collapses and the COVID-19 pandemic.

This research determined that the most influential criteria for selecting and screening sustainable suppliers are capability of supplier/delivery, services, environment protection/management, risk, and green innovation. However, green image, green products, and pollution control are the criteria with minimal influence. Traditional supplier selection criteria such as cost and quality are no longer the primary focus of companies and supply chain professionals. Instead, environmental factors such as green products and pollution control are becoming more critical, indicating a shift towards sustainable supplier selection criteria. We found that risk factors are ranked third among 12 clustering criteria with the average weight (w_{12}^{M}) over 15%. This shows the high importance of risk factors in the realistic clustering of suppliers. Provided that suppliers A1, A4, A9, and A16 have been ranked notably higher than other suppliers in terms of all criteria, ignoring risk factors does not change the final clustering scheme while changing the intervals. However, when these alternatives (suppliers A1, A4, A9, and A16) are not considerably different from others, the clustering scheme changes by ignoring risk factors. This explanation prevails for all those factors with a high importance weight. So, the lower the importance weight of a factor is, the lesser its effect is on the clustering scheme. The fuzzy C-means and subtractive clustering techniques verified the superiority of suppliers A1, A4, A9, and A16 over others.

In terms of costs, buyers no longer look for the lowest price to gain profits, as they have discovered other types of benefits and competitive advantages, such as upsides from protecting the environment with environmentally friendly products and social responsibility outcomes. Focusing on sustainable development objectives, companies can enter new markets to find more customers, which will easily lead to higher profits in economic terms. In the current marketplace, the quality of services is also far more important than the quality of products since consumption strategies have changed, and producers reduce product longevity. Instead, the quality of service has increased, and buyers expect just-in-time delivery to receive goods and services. Overall, companies should focus on environmentally friendly products and socially responsible outcomes while managing costs and maintaining profitability. Companies must integrate risk assessment programs and the evaluation of the collaborations between suppliers into sustainable supply chain management practices. This study suggests that our proposed clustering framework can be used to select sustainable suppliers based on multiple attributes. This method not only safeguards environmental and social resources but also enhances the resilience of supply chains to encounter disruptions by considering risk factors.

5. Conclusion and future research directions

Sustainability issues, especially on sustainable supplier clustering and selection, call for better management of the evaluation process, especially under a fuzzy decision-making environment and with multi-criteria to consider. This paper integrated the risk dimension of the supply chain into the evaluation criteria of the sustainable supplier selection and clustering problem. We implemented fuzzy equivalence relations to cluster a set of sustainable suppliers in the plastic industry. Clustering techniques, in general, and fuzzy equivalence relation clustering, in particular, categorise observations into sub-sets according to their similarities. When the exact information on the evaluation criteria is unavailable, and decision makers rely on uncertain judgments, and when the number of evaluation criteria and alternatives is high, clustering techniques based on fuzzy equivalence relations help managers in their decisions. Managers can significantly reduce the number of alternatives and remove the poorer alternatives using this method. This method is very helpful for circumstances where decision-makers do not possess clear and exact information about the performance of the suppliers and can only state their preferences with linguistic terms. We have assumed 12 dimensions with 60 sub-criteria for the clustering problem. The proposed approach can be used in other multi-attribute applications such as market selection, energy sector selection, vehicle selection, etc. K-means and/or K-nearest neighbours (K-NN) algorithms can be implemented to compare the resulting clusters.

Author contributions

Conceptualization: Reza Kiani Mavi, Navid Zarbakhshnia; Methodology: Reza Kiani Mavi, Navid Zarbakhshnia, Neda Kiani Mavi, Sajad Kazemi; Data collection: Navid Zarbakhshnia, Sajad Kazemi; Formal analysis and investigation: Reza Kiani Mavi, Sajad Kazemi; Writing - original draft preparation: Navid Zarbakhshnia, Neda Kiani Mavi, Sajad Kazemi; Writing - review and editing: Reza Kiani Mavi; Supervision: Reza Kiani Mavi.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.118811.

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