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RESEARCH ARTICLE

Supplier selection in the industry 4.0 era by using a fuzzy cognitive map and hesitant fuzzy linguistic VIKOR methodology

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Abstract
Organizations will be increasingly concerned about maintaining their positions in today's changing world, the high-tech era, and the emergence of innovative technologies because of the industrial revolutions. Everyone has come to believe that to survive and continue their constructive roles, they must achieve competitive advantages by working based on the trends. It is undeniable that the introduction of Industry 4.0 has had a significant impact on enterprises, organizations, and, of course, supply chains. In the meantime, selecting a supplier is one of the main strategic decisions of the organization because choosing the right supplier leads to increasing profitability, improving market competition, better accountability, enhancing product quality, and reducing costs. While the issue of supplier evaluation has been one of the interesting topics for researchers in recent decades, its development in the fourth supply chain generation needs further consideration. In this regard, current technologies in the fourth-generation industrial revolution, methods, and criteria used in previous studies based on industry 4.0 and before that are reviewed separately. By reviewing previous articles and experts' opinions, thirteen sub-criteria considering industry 4.0 have been identified for selecting suppliers in three categories, economic, environmental, and social. The weight of each criterion has been determined using a set of fuzzy cognitive maps (FCMs) and considering the centrality of criteria in the concept of communication networks. To prioritize the suppliers, the hesitant fuzzy linguistic term sets (HFLTS) VIKOR method has been used in hesitant fuzzy linguistic terms. Finally, a case study is introduced to illustrate the effectiveness and usefulness of our integrated methodology and prioritize its four suppliers.

Keywords Supplier selection · Industry 4.0 · Fuzzy cognitive maps · VIKOR · HFLTS

Introduction

During the past three decades, technology has grown quickly and has made many changes in the marketplace and the lives of people (Mokhtarzadeh et al. 2021; Stock and Seliger 2016). Industrial revolutions have been one of the most effective and influential changes in human lives, which were born in the second half of the eighteenth century and have continued to reach the fourth industrial revolution (industry 4.0). Industry 4.0 is based on doing processes by computers without human intervention, named intelligent factories (Alaloul et al. 2020). Achieving high-tech technology causes

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significant changes in supply chain management (SCM) as it has affected the performance of retailers, operating companies, and other supply chains (SC) components. Thus, researchers usually focused on the principles and practices for digitalized SCM and determined its enablers and barriers (Chauhan and Singh 2019). However, industry 4.0 influences the design and operation of the SC (Hofmann et al. 2019). Also, it causes digital and autonomous linkage within companies (Stölzle et al. 2017). In short, all the stages of a typical SC, including supplier, producer, distributor, and retailer will be affected by different aspects of the industry 4.0 revolution (Tjahjono et al. 2017).

In today's global marketplace, organizations are looking for a competitive advantage by focusing on their supply chain (Fallah Lajimi et al. 2020). Purchasing is one of the most vital activities of companies and has a significant impact on product and organizational costs, competition, and overall performance (Matthess et al. 2022). Choosing a suitable supplier leads to reduced operating costs, increased profitability, improved product quality, market competition, and better responsiveness (Abdollahi et al. 2015). Choosing the appropriate supplier can be effective in the organizations' flexibility, stability, and productivity (Hasan et al. 2020). One of the strategic decisions is identifying a suitable supplier in SCM as it affects the cost and the quality of the ultimate product (Safaeian et al. 2019). One of the main goals of supplier selection (SS) is to decrease the risk of buying and develop a relationship between buyers and sellers (Yazdani et al. 2017). As discussed above, supply chains are impacted by the dimensions of industry 4.0 (Frank et al. 2019). With the improvement of technology, intelligence has expanded in various fields, and suppliers, and *the group that directly affects the performance of companies, needs digitalization to embrace the existing conditions* (Özek and Yildiz 2020; Shahsavar et al. 2021). Developments in communication and IT have affected production systems and SS processes (Çalık, 2021). Digitalization has been expanded in all aspects of life due to advanced IT. It is expected to expand in the future, so the degree of adaptation of firms will affect their future success. Some researchers discussed the application of new technologies that change supplier selection criteria (SSC) (Ghadimi et al. 2019). The digitalization of suppliers and the appearance of digital technologies in SS directly affect the performance of companies. Therefore, it is compulsory to focus on the characteristics of suppliers in industry 4.0 and the digital SC (Özek and Yildiz 2020). Supplier selection in industry 4.0 (SS 4.0) is a complicated process that involves many parts of an organization. A great deal of discussion is devoted to the significance of the coordination role between suppliers and its effect on SC performance. For example, some studies revealed the direct impact of coordination on the quality and flexibility of SC performance (Jayaram et al. 2011). Therefore, it appears that the initial step to achieve coordination between the company and its suppliers in the complex and multi-dimensional course of industry 4.0 is to select the appropriate suppliers which are eligible as qualified suppliers based on industry 4.0 characteristics.

Although different frameworks are proposed to identify SSC (Chang et al. 2011; Kar and Pani 2014; Wilson 1994), however, few studies have been done about proposing an adjusted framework of SSC based on the industry 4.0 requirements and features. A new definition of coordination seems necessary in the industry 4.0 era. To achieve coordination between the company and its suppliers, they must work on information flow and relationship building (Singh et al. 2019). There are few attempts to simultaneously determine the weight of the SSC based on the relationships among the criteria in the industry 4.0 era. As a result, this paper is one of the first efforts to illustrate a new structured framework for analyzing the SSC in the digital era. In the current study, a structure is proposed to fill the research gaps of (i) What are the best criteria for selecting a supplier in industry 4.0 based on their casual connections among them? (ii) In the uncertain atmosphere of the digital age, which supplier is deemed to be the best? *A framework that covers all of these issues at the same time, has not been provided yet*.

To handle the mentioned problem, in this study, an attempt has been made to provide SSC appropriate to the characteristics of industry 4.0 by considering uncertainty and interdependence between criteria. Considering the uncertainty in data collection and the interdependence between the criteria are contrary to the real world. First, this paper compares SSC in the traditional era and the industry 4.0 era for a better understanding of the process of changing criteria. Then, based on the expert's idea, the selected criteria and existing relationships among them are used to identify the criteria's weight. A fuzzy cognitive map (FCM) is organized to simultaneously identify and weigh the suggested criteria of SS 4.0 based on uncertainty in data collection and interdependence among the SSC. Furthermore, hesitant fuzzy linguistics is used to solve the decision-making processes' uncertainties and obtain experts' opinions. The experts' opinions can be vague and hard to express with exact numerical data. When the experts imply ambiguous linguistic terms for judgment, HFLTS can be an efficient fuzzy model. In fact, due to their unique efficiency and flexibility in describing uncertainty, the hesitant fuzzy linguistic term sets (HFLTSs) are used to elicit the decision makers' linguistic preferences (Isik and Kaya 2022). The VIKOR method for compromise ranking, which is an effective tool for MCDM, determines a compromise solution by providing a maximum "group utility" for the "majority" and a minimum of "individual regret" for the "opponent" (Geng et al. 2020). Especially when the experts are unable to comprehend how to display their preferences at the start of system design. To sum up, the main contribution of this paper is to present a novel model combining FCM and HFLTS VIKOR to reduce the ambiguities of experts' ideas, reshape them, and clarify the possible issues in the future perspective of Industry 4.0 levels in the context of linguistic evaluation. Moreover, this model can provide insight into the criteria of SS 4.0. While researchers have paid much attention to SS, there needs to be more effort to solve this problem in industry 4.0 with fuzzy cognitive map modeling. This paper attempts to weight SSC 4.0 by using FCM and rank suppliers by the HFLTS VIKOR method. Scholars and managers will be able to use the selected SSC to increase their performance in selecting the best supplier.

The rest of the paper is organized as follows. The literature of relevant works is discussed in the "Literature review" section, and the preliminaries are reviewed in the "Preliminaries" section by introducing the fundamental concept of the hesitant fuzzy linguistic approach. Then, the proposed approach integrating the FCM and HFLTS VIKOR methods for ranking the supplier in industry 4.0 is discussed in the "Methodology" section, which is implemented by the real statistics for the electronics industry in the "Case study" section. The "Conclusion" section provides the conclusion of the paper with a contribution to practice, managerial and theoretical insights, and a subsection on limitations and future course of action for the research area.

Literature review

To focus on the main features of the organization, companies must outsource their activities, including manufacturing and assembly, so the purchase and management of materials will be necessary (Vonderembse and Tracey 1999). Both operational and strategic advantages can be expected from outsourcing (Lankford and Parsa 1999). SS has been a significant issue in SCM. Purchasing is one of the significant roles in the organization as it can substantially impact the outcomes of the core functions (van Weele 2002). Purchasing has a vital role in achieving competitive advantage in dynamic and impermanent markets. Many managers have identified the purchase as an important strategic device for achieving competitive advantage in the organization (Mohammed et al. 2019; Quayle 2006). In today's complex world, the lifespan of products is shortened, so having new suppliers to diversify products is a constant priority for companies. An effective supplier provides services and products based on customers' demands (Hamdan et al. 2019). Suppliers play a substantial role in advancing supply chain strategy. Studies revealed a direct relationship between supplier practices and corporate performance (Jajja et al. 2016). The impact of suppliers' performance on organizational strategies is also studied (Gupta and Narain 2012). The importance of suppliers has also enhanced the performance of outsourcing as a strategic initiative that directly affects corporate performance (Lee et al. 2018). Therefore, suppliers can be considered strategic partners of an organization with a high direct and indirect impact on organizational performance. Confronting this strategic decision, scholars proposed using MCDM for selecting suppliers. Lu et al. (2021) illustrated that most of the researchers implemented the Fuzzy MCDM in SCM issues based on 301 studies which he reviewed until 2020. For instance, hesitant fuzzy linguistic (HFL) AHP is applied for ranking the Supply Chain Analytics (SCA) alternatives (Büyüközkan and Güler 2021). Studies on the topic of SS include two basic issues, selection criteria and selection methods (Ghodsypour and O'Brien 1998). Different SSC is identified according to the environmental conditions and suppliers' features. Table 1 contains traditional criteria and methods used in recent articles.

Due to the competitiveness of businesses and the emergence of many innovations, organizations are moving toward the last industrial revolution. The direct connection between machines is what comes from industry 4.0. This revolution is a great help for cooperation among suppliers, manufacturers, and customers to establish transparency from entering to ending the production process (Tjahjono et al. 2017). Many features have been defined by industry 4.0. It can improve the efficiency of the SC and efficient management by creating a reliable industrial infrastructure and workforce training and increasing (Hofmann and Rüsch 2017; Zhou et al. 2016). Thus, industry 4.0 technologies have followed key impacts such as increased flexibility, productivity, and quality, and decreased lead times, costs, and development time (Asif et al. 2022; Moeuf et al. 2018; Shafiq et al. 2015). In addition, industry 4.0 is useful for raising the level of data sharing through the supply chain, the transparent lifecycle of a product, and gathering new information (Esmaeilian et al. 2020). Industry 4.0 will increase operational efficiency with the improvement of products or services. However, the emerging industry 4.0 has forced us to address the issue of SS in this age (Özek and Yildiz 2020). The necessity of revising the framework and structure of SS 4.0 is due to the fundamental changes it caused (Özek and Yildiz 2020). Several articles have attempted to provide a framework for SS 4.0, and the details of each approach and proposed criteria are presented in Table 2.

There is an accepted agreement among scholars and practitioners to consider SS as a multi-criteria problem influenced by different factors (Amid et al. 2011). There are various quantitative and qualitative criteria for selecting a

Table 1 Traditional supplier selection methods and criteria

(Author, year)	Method	Criteria
(Beikkhakhian et al. 2015)	Fuzzy TOPSIS-AHP methods	Uncertainty minimization, customer satisfaction, lead time minimization, cost minimization, delivery speed, data accuracy, price, transportation, information technology tools, quality improvement
(Lee et al. 2015)	Fuzzy TOPSIS	IT infrastructure, quality control, language, license/certification/award, management and strategy, product diversity, customer relations, R&D capability, environmental regulations, product price, history, after-sales service, delivery speed, production facility/capacity, make flexibility, delivery reliability, source flexibility, financial status, agile customer responsiveness, geographical location, collaboration with partners, delivery flexibility, reputation, training program, safety regulations
(Rajesh and Ravi 2015)	AHP and ANP	Cost, quality, level of collaboration, flexibility, supply chain visibility, supply chain velocity, risk awareness, vulnerability, technological capability, supply chain continuity management, safety, research and development, concern for the environment
(Dweiri et al. 2016)	AHP	Price, quality, delivery, service
(Lima-Junior and Carpinetti 2016)	Fuzzy QFD	Cost reduction, safety programs, demand change, honesty, competitive price, solid waste, the potential for collaboration, returns handling capability, human resource management skill, delivery in full on time, ease of communication, environmental certification, product conformance, geographical proximity, commitment to quality improvement, responsiveness, design capability, measurement tools, and methods, structure for information sharing, quality certification
(Liao et al. 2016)	Multi-segment goal programming, fuzzy additive ratio assessment, fuzzy AHP	Quality service, purchase cost, delivery performance, environment skill, and technology capability
(Hamdi et al. 2016)	Hybrid fuzzy AHP-fuzzy PROMETHEE	Product pricing, financial stability, investment in R&D, product/service quality, political/economic stability delivery reliability, past performance, reputation in the market, contractual commitments, output flexibility, geographical location, labor issues, visibility
(Hamdan and Cheaitou 2017)	Fuzzy TOPSIS	Stock availability, green image, compliance with government, environment protection, delivery time, quality, design for environment, cost, payment term
(Qin et al. 2017)	Interval type-2 fuzzy sets TODIM	Green image, staff environmental training, green product innovation, green competencies, pollution production, quality management, environment management, total product life cycle cost, resource consumption, use of environmentally friendly technology
(Luthra et al. 2017)	An integrated AHP and VIKOR	Price, profit, quality, transportation cost, technological and financial capability, flexibility, environmental competencies, delivery and service of product, information disclosure, production facilities, and capacity, the rights of stakeholders, green packing and labeling, green design and purchasing, environment management systems, green manufacturing, green R&D, green management, occupational health and safety systems, environmental costs, lead time required, the interests and rights of employees, waste management and pollution prevention
(Gören 2018)	Taguchi loss functions, integrating fuzzy DEMATEL	Productivity, capacity of the supplier, friendly product design, price, lead time, quality, production technology, long-term relationship—continuity, occupational health and safety management system, environmental management system, responsiveness, supportive activities, environmental, resource consumption
(Lo et al. 2018)	Best–worst method and fuzzy TOPSIS and fuzzy multi-objective linear programming (FMOLP)	Product quality, environmental performance, innovation capability, service flexibility, labor intensive, green logistic, financial stability, information safety, supplier reputation

Table 1 (continued)

(Author, year)	Method	Criteria
(Mohammed et al. 2018)	Fuzzy AHP, fuzzy TOPSIS	Costs, technology capability, livestock healthiness/meat freshness, environment management system, delivery reliability, safety, waste management, rights and health of employees, pollution production, information disclosure, and staff development
(Nourmohamadi Shalke et al. 2018)	TOPSIS	Quality, worker safety, health, delivery, loyalty, technical capability, cost, training, environmental management system, education and community development, occupational health and safety management system, pollution, and greenhouse gas emission
(Kumar et al. 2019)	Taguchi loss function, TOPSIS, and AHP	Quality, delivery, price, service
(Mohammed et al. 2019)	Fuzzy AHP-fuzzy TOPSIS, fuzzy multi-objective optimization model	Information disclosure, waste management, costs, staff development, green environment management systems pollution production, rights and health of employees, social safety, delivery reliability, product quality, technology capability
(Yazdi et al. 2022)	COPRAS and SWARA	Positive image, new products, exchange of knowledge, commitment, novelty, quality, cost, reputation, flexibility, R&D, technical capability, technical experts, compatibility, relation, technology
(Yazdani et al. 2022)	SWARA and LBWA, MARCOS	Climate and weather conditions, quality, viticulture practices, training and trellising, ecological practices, the flexibility of delivery, offered price, pollution control, environmental management system, social responsibility, and sustainability of the suppliers
(Wu et al. 2021)	FMEA and EWM, DEMATEL	Price, quality, prompt delivery rate, transportation loss, supply capacity

suitable supplier. Keshavarz Ghorabaee et al. (2017) illustrated a wide variety of studies in SS problems by using the multi-criteria decision-making (MCDM) method, and as a result, showed the TOPSIS and the AHP are applied as the most popular methodologies (Ali et al. 2021). In addition, the combination of quantitative and qualitative data based on the judgment will cause uncertainty in the SC (Yu et al. 2013). Moreover, incomplete information on SC levels also leads to uncertainty about the problem, such as different opinions of experts and uncertainty about the quality of available information (Schramm et al. 2020). Fuzzy set theory can be applied to uncertainty in the evaluation information (Ghadimi et al. 2019; Liu et al. 2020). Also, some researchers applied the fuzzy OR method to solve problems based on uncertain environments, and as a result, they enhanced the efficiency of the system (Dolatabad et al. 2022; Lu et al. 2021). Kayapinar Kaya and Aycin (2021) introduced a framework based on industry 4.0 by identifying four main criteria and twenty-one subcriteria. The best–worst method (BWM) and VIKOR were applied to select a sustainable supplier for a textile manufacturing company in Pakistan. Also, some scholars applied BWM and VIKOR methodologies to choose sustainable suppliers in the context of circular economy and industry 4.0 initiatives (Sarpong et al. 2021). In addition, Fallahpour et al. (2021) applied the Fuzzy-BMW and fuzzy inference system (FIS) for evaluating the suppliers based on sustainability criteria in industry 4.0. Chen et al. (2020) introduced a framework for identifying supplier criteria and using a hybrid rough-fuzzy DEMATEL-TOPSIS method for sustainable SS by considering a smart supply chain. To determine criteria weights, the DEMATEL method and for ranking suppliers, the TOPSIS method was used in an uncertain environment. Sachdeva et al. (2019) provided a hybrid intuitionistic fuzzy entropy weight-based for modeling SS 4.0 by using the TOPSIS method. This paper uses five criteria of cost, delivery delay, rejection rate, Industry 4.0 Tech-Enabled, and relationship. Ghadimi et al. (2019) referenced the role of the development of communication information systems and its impression on the movement of supply chains 4.0 and reviewed the issue evaluation of sustainable suppliers in supply chains. Also, considering the sustainability dimensions, the paper uses three main dimensions, environmental, economic, and social dimensions to SS (Babgohari et al. 2022). Çalık (2021) paid attention to industry 4.0 green supplier evaluation by mixing AHP and TOPSIS methods based on the Pythagorean fuzzy environment. Hasan et al. (2020) used TOPSIS- triangular fuzzy method in logistic 4.0 and solved the SS problem. Özek and Yildiz (2020), in digital SS, used Interval Type-2 Fuzzy TOPSIS. Table 2 illustrates a summary of the reviewed paper on SS 4.0.

Table 2 Industry 4.0 supplier selection methods and criteria

Author	Method	Criteria
(Liao et al. 2019)	BWM and ARAS under hesitant linguistic fuzzy	Digital engagement, degree of information sharing, flexibility, financing threshold, scale of digital collaboration, service quality, and financing efficiency
(Ghadimi et al. 2019)	Multi-agent systems	Cost, quality, delivery/service, green image, green competencies, technical capability, pollution control, health and safety, and employment and employment methods
(Sachdeva et al. 2019)	TOPSIS, entropy, intuitionistic fuzzy	Price/cost, rejection rate, technological capabilities, delivery delay, relationship
(Chen et al. 2020)	Hybrid rough-fuzzy DEMATEL-TOPSIS	Smart working environment, smart delivery, ensuring the rights of stakeholders, cost reduction, enhancement of supply flexibility, green purchasing, green design, green and smart manufacturing, employee development in a smart atmosphere, green and smart logistics, internal management awareness, product quality improvement, social activities
(Hasan et al. 2020)	Fuzzy TOPSIS	Cost, lead time variability, production capacity, prepositioned inventory level, supply chain density, digitalization, automation disruption, traceability, supply chain complexity, restorative capacity, supplier's resource flexibility, re-engineering, cyber security risk management, information management, supply chain visibility, supplier reliability, rerouting, agility, level of collaboration
(Çalık, 2021)	A novel Pythagorean fuzzy AHP and fuzzy TOPSIS	Automated guided vehicles, robotics, IoT and CPS, environmental control, big data analytics, service level, cloud computing, lean automation, 3D printing and augmented reality, green design, green image, Quality 4.0
(Kayapinar Kaya and Aycin 2021)	Interval type 2 fuzzy AHP and COPRAS-G	Cost/price, quality, delivery, internet of things (IoT) implementation, capacity, intelligent transportation systems such as GPS, smart warehouse and shelving system, employee training, RFID and dynamic sensors, big data and cloud computing, use of the autonomous machine

According to the introduction of different criteria, there is still no agreement on the criteria, and they should be localized according to each area. Compared to the two tables provided above, SSC has moved towards digitalization, and quantitative methods have received more attention (Aouadni et al. 2019). There are several articles on this topic, but by updating research, the selection of suppliers in industry 4.0 has been considered. SSC needs to fit in with this industrial revolution and needs to focus more on criteria. Few authors have paid attention to the relationship, which existed between criteria in the new industrial revolution. If firms know more about the criteria, they can do better. One of the best ways to analyze and evaluate systems is fuzzy cognitive maps (FCM). Evaluating industry 4.0 criteria with fuzzy cognitive maps is an issue that most researchers did not pay attention to. In this paper, after reviewing SSC based on expert opinions, a set of suitable SSC for industry 4.0 are identified and their relationship is explored using fuzzy cognitive maps. The proposed framework can be beneficial for companies to achieve a better comprehension of industry 4.0 SSC to help them in selecting more appropriate ones.

Preliminaries

The hesitant fuzzy linguistic VIKOR methodology has been used in this research, which has more complexities than the classical VIKOR method for solving the problem. To explicate these complexities, in this section, an attempt has been made to explain the basic concepts related to the hesitant fuzzy linguistic approach and VIKOR method. It should be noted that the methodology will be fully explained in the "Methodology" section.

Basic concepts related to the hesitant fuzzy linguistic approach

In the classic MCDM models, precise values are used for evaluation. To make it more efficient, these models should illustrate the situation as close as possible to the real world. Incomplete information or knowledge, as well as complexity and ambiguity, may make decision-making difficult (Liao et al. 2017). Linguistic information is relevant to cognitive processes; hence, decision-makers may convey their thoughts more effectively. The fuzzy linguistic methodology is a common procedure for modeling linguistic information. Based on this technique, each linguistic value is characterized by a syntactic and a semantic value (Herrera and Herrera-Viedma 2000). To do so, Xu (2005) proposed a discrete term set, which represents the value of a linguistic variable.

In the linguistic term set, only one term expresses the uncertain information, but when experts are hesitant, choosing multiple terms can help (Büyüközkan and Güler 2021). To deal with this problem, Torra (2010) introduced the concept of Hesitant fuzzy sets (HFS). Rodriguez et al. (2012) illustrated the fuzzy linguistic approach and the HFS, HFLTS is defined as follows:

- Definition 1. Assume $S = \{s_0, \ldots, s_g\}$ denoted a linguistic term set and L and U as two integers that $L, U \in \{0, 1, \ldots, g\}$ and $L \le U$. The HFLTS is denoted as $\vartheta = \{s_L, s_{L+1}, \ldots, s_U\}$, where s_L is the lower, and s_U is the upper spring of ϑ. Please notify that ϑ is a noncontiguous set on S (Wu and Xu 2016). One possible distribution for ϑ on S has been introduced to converse with an extensive range of hesitant information. Wu and Xu (2016) defined a possible distribution as follows:
- Definition 2. Assume $S = \{s_0, \ldots, s_g\}$. $\vartheta = \{s_L, s_{L+1}, \ldots, s_U\} \in H_S$ is an HFLTS. The possible distribution for ϑ on S is shown by $P = \{p_0, p_1, \ldots, p_l, \ldots, p_g\}$, where p_l is given by

$$p_l = \begin{cases} 0 l = 0, 1, \ldots, L-1 \\ \frac{1}{U-L+1} l = L, L+1, \ldots, U \\ 0 l = U+1, \ldots, g \end{cases} \tag{1}$$

  and p_l expresses the possibility that the alternative has an assessment value s_l provided by the expert.

An HFLTS with an extra possible distribution writing in pairs. For instance, if $S = \{s_0, s_1, \ldots, s_6\}$, then $\vartheta = \{s_2, s_3, s_4\} \in H_S$ with the associated possible distribution P = (0, 0, 0.3, 0.4, 0.3, 0, 0) being identical to $\{s_2(0.3), s_3(0.4), s_4(0.3)\}$. For clarity, $\vartheta \in H_S$ with a possibility distribution is called PDHFLTSs. The linguistic term set S is identified as only $P = P(\vartheta)$ is required to show a PDHFLTS without any doubt.

- Definition 3. Let $S = \{s_0, \ldots, s_g\}$ and $\vartheta \in H_S$. The possibility distribution resembling ϑ is $P = \{p_0, p_1, \ldots, p_l, \ldots, p_g\}$. Then the expected value (or the mean) for ϑ which is shown by P can be defined as follows (Wu and Xu 2016):

$$E(\vartheta) = \sum_{l=0}^{g} NS(S_l) p_l. \tag{2}$$

  where $NS(S_l)$ is the numerical scale for the linguistic term S_l.
- Definition 4. Consider $S = \{s_0, \ldots, s_g\}$, $\vartheta = \{s_L, s_{L+1}, \ldots, s_U\} \in H_S$ and $P = \{p_0, p_1, \ldots, p_l, \ldots, p_g\}$. Then the variance for ϑ shown by P can be outlined as follows (Wu and Xu 2016):

$$Var(\vartheta) = \sum_{l=0}^{g} (NS(S_l) - E(\vartheta))^2 p_l. \tag{3}$$

- Definition 5. Suppose $\vartheta 1, \vartheta 2 \in HS$, then the comparing operation over $\vartheta 1$ and $\vartheta 2$ can be defined as (Wu and Xu 2016):

(i) if $E(\vartheta 1) < E(\vartheta 2)$, then $\vartheta 1 < \vartheta 2$, max $\{\vartheta 1, \vartheta 2\} = \vartheta 2$ and min $\{\vartheta 1, \vartheta 2\} = \vartheta 1$.
(ii) if $E(\vartheta 1) = E(\vartheta 2)$, then

(a) if $Var(\vartheta 1) < Var(\vartheta 2)$, then $\vartheta 1 > \vartheta 2$;
(b) if $Var(\vartheta 1) = Var(\vartheta 2)$, then $\vartheta 1 = \vartheta 2$.

- Definition 6. Assume $A_H = \{\vartheta 1, \ldots, \vartheta n\}$ is a set of PDHFLTSs, where $w = \{w_1, \ldots, w_n\}$ is their associated weight vector. Each ϑ_k has its possible distribution expressed as $P^k = P^k_0, \ldots, P^k_l, \ldots, P^k_g)$. The hesitant fuzzy linguistic weighted average (HFLWA) operator is defined by a possible distribution $P = \{p_0, p_1, \ldots, p_l, \ldots, p_g\}$ on S (Wu and Xu 2016).

$$HFLWA(\vartheta_1, \ldots, \vartheta_n) = HFLWA(P^1, \ldots, P^n) \triangleq (p_0, \ldots, p_l, \ldots, p_g) \tag{4}$$

  where p_l is calculated by

$$p_l = \sum_{k=1}^{n} w_k p^k_l. \tag{5}$$

- Definition 7. Let us assume that $\vartheta, \eta \in H_S$ or $\vartheta, \eta \in EH_S$. Let $P = (p_0, p_1, \ldots, p_g)$ and $Q = (q_0, q_1, \ldots, q_g)$ $(g \ge 1)$ be the possible distributions resembling ϑ and η, respectively. Then the length between ϑ and η based on P and Q is showed as below (Wu et al. 2019):

$$d_{pd}(\vartheta, \eta) = \frac{1}{g} |E(\vartheta) - E(\eta)| = \frac{1}{g} \left| \sum_{l=0}^{g} NS(S_l) p_l - \sum_{l=0}^{g} NS(S_l) q_l \right| \tag{6}$$

Basic concepts related to the VIKOR method

One of the multi-attribute decision analysis methodologies is the VIKOR method that has been proposed by Opricovic and Tzeng (2004). Based on non-commensurable and conflicting attributes, this method chooses the best compromise solution from a set of solutions. VIKOR is an appropriate tool for decision-making, especially, where the preferences of the experts are not clear in commence of the system design. As obtained compromise solution introduces a minimum individual regret of the "opponent" and a maximum "group utility" of the "majority," which can be applied by the decision-makers. the experts define their preferences based on negotiations by considering the weight of each criterion (Opricovic and Tzeng 2004).

This method calculates the worst f_j^- and the best f_j^+ values of all criteria to be able to compute Si and Ri values for final Qi rankings. The minimum Qi value is assigned the highest suitable and the maximum Qi value is not suitable. The VIKOR method has been investigated and improved over time by many researchers (Liao et al. 2015). HFLTS VIKOR is one new extension of this method, that forms the linguistic representation model and demonstrates human cognitions more flexibly (Liao et al. 2015). In this paper, the HFLTS VIKOR method is developed, which is illustrated in the 3.4 section.

Methodology

This section addresses the proposed approach integrating the FCM and HFLTS VIKOR methods to rank the supplier in industry 4.0. In Fig. 1, the general concept of the proposed method is illustrated. Given the further explanations provided in the methodology section about the methods, the proposed approach can be defined in three phases.

Identifying

In the first phase, the selected criteria by the literature (that is illustrated in Table 2) were reviewed by experts in focus group meetings. Subsequently, finalized criteria for SS 4.0 were chosen. The output of this phase provides set $A=\{A_1, A_2, \ldots, A_m\}$ of m possible supplier alternatives, and a set $C=\{C_1, C_2, \ldots, C_n\}$ of n criterion of industry 4.0 suppliers.

Fuzzy cognitive maps

The FCM technique is used to compare the multiple ways in which the criteria correlate with one another, and the Mental Modeler software is used to depict the map of the connection between the criteria based on the expert's judgment. The main problem in this phase is the weight of criteria, which can be determined by considering the normalized centrality of these relationships. Fuzzy cognitive maps can be applied for quantitative modeling. Fuzzy cognitive maps are fuzzy-oriented diagrams introduced after the cognitive map method (Axelrod 2015; Kosko 1986). FCM is an integrating method of fuzzy logic and a cognitive map (Erkan and Uygun 2020). This model depicts the behavior of a physical system using nodes and edges (Felix et al. 2019). FCMs display causal reasoning among criteria (Bevilacqua et al. 2020) These days, FCMs have entered most research fields and complex systems (Erkan and Uygun 2020). For instance, it is used to analyze and evaluate systems in political and social sciences, healthcare, business, agriculture, and the environment and to solve the problem with numerous solutions such as modeling, decision support systems, classification, scenario, etc. (Kiraz et al. 2020). FCM is used in many areas—medical science, business, environment, energy, and political and social science—with many solutions—decision support systems, classification, modeling, and scenario planning (Grouinpos 2019; Yue et al. 2019). For instance, a medical area with decision support systems is used by Amirkhani et al. (2018), a business area with decision support systems is used by Azar and Mostafaee Dolatabad (2019) and Nasserzadeh et al. (2008), an energy area with scenario planning is used by Papageorgiou et al. (2020). The FCMs method is chosen to define the relationship between the criteria of SS 4.0 with a modeling solution.

The suggested model has been combined with FCMs to evaluate SSC 4.0 based on the current situation and predict upcoming conditions. Strategic managers of companies can concentrate on certain criteria for noticeable improvement. A simple FCMs structure is displayed in Fig. 2. FCMs include three types of relationships: positive relationships, negative relationships, or lack of relationships. Positive relationship among the concept variables C_i and C_j, illustrate with $W_{ij} > 0$, $W_{ij} < 0$ for negative relationship, and finally, $W_{ij} = 0$ shows there is no relation between C_i and C_j concept variables (Tsadiras 2008).

The concepts $C_1, C_2, C_3, \ldots, C_n$ represent A, as the state vector of the system. Determining the period is an important part of creating the state vector as the A state vector displays the existing position (Papageorgiou et al. 2011). The main components of cognitive maps include the nodes, the arc between the nodes, and the mark on these arcs. Nodes represent concepts that describe the system, Arcs represent cause-and-effect relationships between concepts that weigh $[-1, +1]$ and the sign on the arcs indicates the type of causality between the concepts. For the keeping method, the primary vector and weight matrix must be defined. Depicted diagram of FCMs is illustrated in Fig. 3.

- identifying A^k vector.
- obtain $A^{(k+1)}$ as follow:

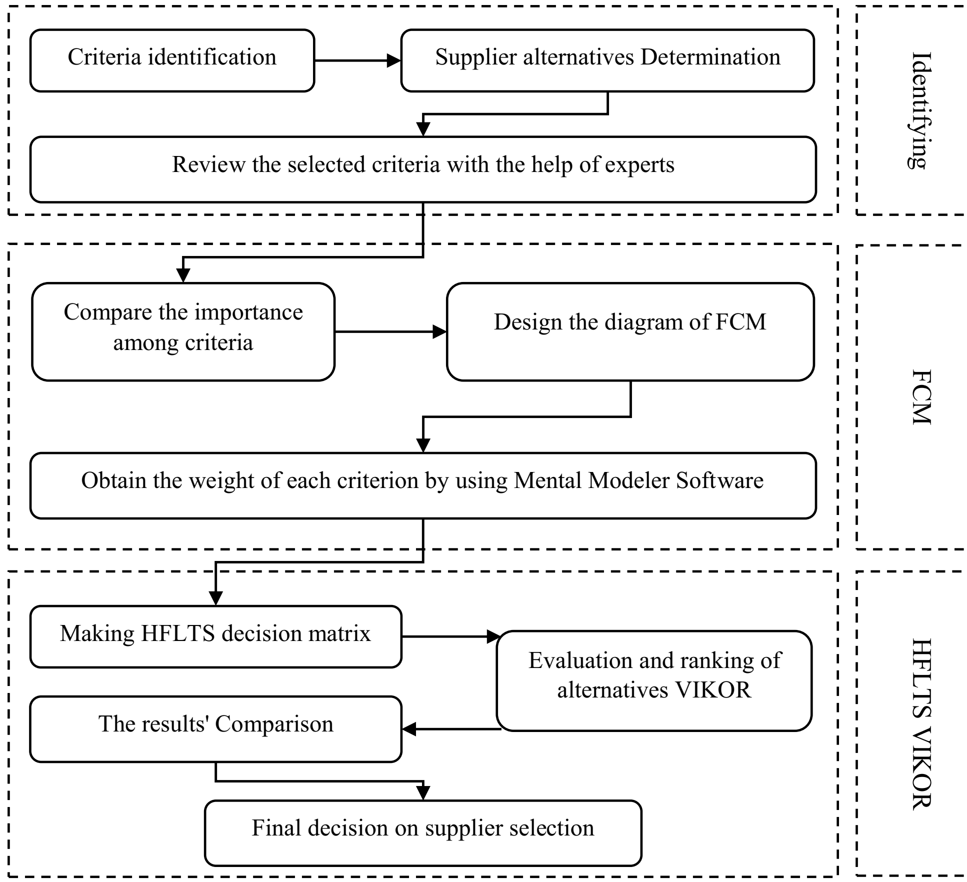

Fig. 1 Decision-making process by the proposed approach

$$A_i^{(k+1)} = f(\left(A_i^{(k)}\right) + \sum_{j=1, j\neq 1}^{N} W_{ij} \times (A_i^{(k)})) \tag{7}$$

– Obtain the sigmoid function.

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{8}$$

– Obtaining $A^{(k+1)}$ as the new, $A^{(k)}$ vector.

– Repeating the algorithm until $A^{(k+1)} - A^{(k)} < 0.001$.

HFLTS VIKOR

To guarantee customer satisfaction and the competitiveness of the supply chain, the proper suppliers must be picked. The VIKOR method presents a multi-criterion ranking based on a specific measure of the distance

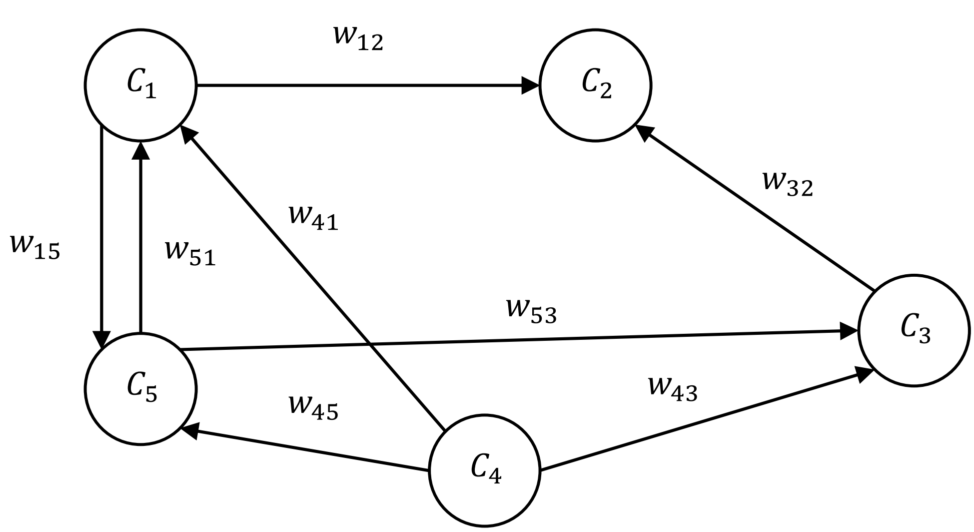

Fig. 2 Fuzzy cognitive map sample (Groumpos 2010)

between the actual solution and the ideal solution. On the other hand, in certain instances, confusion might be caused by a lack of knowledge about the event, and even specialists can have doubts about their assessments (Isik and Kaya 2022). HFLTS is an effective model for expressing uncertain information; however, the model's flexibility makes it problematic to aggregate HFLTS of varying durations (Isik and Kaya 2022). Implementing the VIKOR method based on the HFLTS context for ranking has been done by Liao (Liao et al. 2015).

In this part, the VIKOR method is developed into the HFLTS VIFOR method by placing HFLTS definitions (in the "Basic concepts related to the VIKOR method" section). For this purpose, the HFLTS VIKOR procedure is illustrated in Fig. 4.

- Normalization of the individual decision matrix. *Neg* operator is used to change all values of cost into values of benefit.

$$Neg(\vartheta) = \left\{Neg(s_L), Neg(s_{L+1}), \ldots, Neg(s_U)\right\} \tag{9}$$

The normalized Decision matrix of DM_k is defined as $R_k = (r_{ij}^{(k)})_{n\times m}$.

- Fetch the importance weights of decision makers.
- Aggregation in group decision-making.

$$HFLWA\left(r_{ij}^{(1)}, \ldots, r_{ij}^{(t)}\right) = (P_{ij,0}^{c}, \ldots, P_{ij,l}^{c}, \ldots, P_{ij,g}^{c}), \tag{10}$$

where $P_{ij,l}^{c}$ is gained by

$$P_{ij,l}^{c} = \sum_{k=1}^{n} \lambda_k P_{ij,l}^{(k)}. \tag{11}$$

- Decide the worst f_j^- and the best f_j^+ values for all the attributes.

$$f_j^+ = \max_i r_{ij}^c, j = 1, 2, \ldots, m. \tag{12}$$

$$f_j^- = \min_i r_{ij}^c, j = 1, 2, \ldots, m. \tag{13}$$

- Compute the values for S_i and R_i.

$$S_i = \sum_{j=1}^{m} w_j \frac{d(f_j^+, r_{ij}^c)}{d(f_j^+, f_j^-)}, i = 1, 2, \ldots, n. \tag{14}$$

$$R_i = \max_j \{w_j \frac{d\left(f_j^+, r_{ij}^c\right)}{d\left(f_j^+, f_j^-\right)}\}, i = 1, 2, \ldots, n. \tag{15}$$

- Calculate the distance function based on the resembling possibility distributions.

$$d\left(f_j^+, r_{ij}^c\right) = \frac{1}{g}\left|E\left(f_j^+\right) - E\left(r_{ij}^c\right)\right| = \frac{1}{g}\left|\sum_{l=0}^{g} NS(S_l)p_l^{f_j^+} - \sum_{l=0}^{g} NS(S_l)q_l^{r_{ij}^c}\right| \tag{16}$$

- Calculate the values of Q_i.

$$Q_i = v\frac{S_i - S^-}{S^+ - S^-} + (1-v)\frac{R_i - R^-}{R^+ - R^-}, i = 1, 2, \ldots, n. \tag{17}$$

where $S^+ = max_i S_i$, $S^- = min_i S_i$, $R^+ = max_i R_i$, $R^- = min_i R_i$, and v is a weight for the "the most of criteria" strategy, also 1—v is the weight of "the individual regret".

- Rank the preferences in decreasing order by sorting S_i, R_i, and Q_i.
- Offer a compromise solution. If the following two conditions are satisfied, the alternative $X^{(1)}$ using the measure Q is best ranked:

$Cond_1$. Acceptable advantage

$$Q\left(X^{(2)}\right) - Q\left(X^{(1)}\right) \geq DQ = \frac{1}{n-1}, \tag{18}$$

Fig. 3 FCMs algorithm (Papageorgiou et al. 2011)

- identifying A^k vector.
- obtain $A^{(k+1)}$ as follow:

$$A_i^{(k+1)} = f(\left(A_i^{(k)}\right) + \sum_{j=1, j\neq 1}^{N} W_{ij} \times (A_i^{(k)})) \tag{7}$$

- Obtain the sigmoid function.

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{8}$$

- Obtaining $A^{(k+1)}$ as the new, $A^{(k)}$ vector.
- Repeating the algorithm until $A^{(k+1)} - A^{(k)} < 0.001$.

Fig. 4 HFLTS VIKOR procedure (Wu et al. 2019)

- Normalization of the individual decision matrix. *Neg* operator is used to change all values of cost into values of benefit.

$$Neg(\vartheta) = \{ Neg(s_L), Neg(s_{L+1}), \dots, Neg(s_U)\} \tag{9}$$

The normalized Decision matrix of DM_k is defined as $R_k = (r_{ij}^{(k)})_{n \times m}$.

- Fetch the importance weights of decision makers.
- Aggregation in group decision-making.

$$HFLWA\left(r_{ij}^{(1)}, \dots, r_{ij}^{(t)}\right) = (P_{ij,0}^{c}, \dots, P_{ij,l}^{c}, \dots, P_{ij,g}^{c}), \tag{10}$$

where $P_{ij,l}^{c}$ is gained by

$$P_{ij,l}^{c} = \sum_{k=1}^{n} \lambda_k P_{ij,l}^{(k)}. \tag{11}$$

- Decide the worst f_j^- and the best f_j^+ values for all the attributes.

$$f_j^+ = \max_i r_{ij}^c, j = 1, 2, \dots, m. \tag{12}$$

$$f_j^- = \min_i r_{ij}^c, j = 1, 2, \dots, m. \tag{13}$$

- Compute the values for S_i and R_i.

$$S_i = \sum_{j=1}^{m} w_j \frac{d(f_j^+, r_{ij}^c)}{d(f_j^+, f_j^-)}, \qquad i = 1, 2, \dots, n. \tag{14}$$

$$R_i = \max_j \{w_j \frac{d\left(f_j^+, r_{ij}^c\right)}{d\left(f_j^+, f_j^-\right)}\}, \qquad i = 1, 2, \dots, n. \tag{15}$$

- Calculate the distance function based on the resembling possibility distributions.

$$d\left(f_j^+, r_{ij}^c\right) = \frac{1}{g}\left|E\left(f_j^+\right) - E\left(r_{ij}^c\right)\right| = \frac{1}{g}\left|\sum_{l=0}^{g} NS(S_l) p_l{}^{j^+} - \sum_{l=0}^{g} NS(S_l) q_l{}^{r_{ij}^c}\right| \tag{16}$$

- Calculate the values of Q_i.

$$Q_i = v\frac{S_i - S^-}{S^+ - S^-} + (1 - v)\frac{R_i - R^-}{R^+ - R^-}, \qquad i = 1, 2, \dots, n. \tag{17}$$

where $S^+ = max_i S_i$, $S^- = min_i S_i$, $R^+ = max_i R_i$, $R^- = min_i R_i$, and v is a weight for the "the most of criteria" strategy, also 1 - v is the weight of "the individual regret".

- Rank the preferences in decreasing order by sorting S_i, R_i, and Q_i.
- Offer a compromise solution. If the following two conditions are satisfied, the alternative $X^{(1)}$ using the measure Q is best ranked:

Cond$_1$. Acceptable advantage

$$Q\left(X^{(2)}\right) - Q\left(X^{(1)}\right) \geq DQ = \frac{1}{n-1}, \tag{18}$$

Cond$_2$. Acceptable stability in making any decisions. Alternative $X^{(1)}$ must also be ranked best by X_S and/or X_R. $X^{(1)}$ and $X^{(2)}$ are the compromise solutions if only condition *Cond*$_2$ is not true.

Cond$_2$. Acceptable stability in making any decisions. Alternative $X^{(1)}$ must also be ranked best by X_S and/or X_R. $X^{(1)}$ and $X^{(2)}$ are the compromise solutions if only condition *Cond*$_2$ is not true.

The HFLTS VIKOR method is carried out to prioritize the identified suppliers concerning the different weights of the criteria. The inputs of the HFLTS VIKOR method include the output of the first (the set of alternatives and criteria) and the second phase (the obtained weights of the criteria). According to Figs. 1 and 4, after developing the decision matrix, and applying the weights of criteria in the normalized matrix, a weighted normalized matrix is obtained. Using Eq. (10) to (17), the Q_i, S_i, and R_i of each alternative are calculated. Finally, if the conditions presented in Eq. (18) are satisfied, the alternative prioritization is conducted.

Case study

In this section, the data obtained from academic and industrial experts are analyzed. First, a clarification of the problem and considered criteria are discussed. Then, the weights of the selected criteria are determined using fuzzy cognitive maps and then the suppliers are ranked using the HFLTS VIKOR method. These steps are explained in the following subsections.

Identifying

This part applies a case study in the electronics industry to the SS process from the industry 4.0 window. For this purpose, an electronic company that produces air conditioners or air purifiers was selected as a case study. This company currently employs around 200 employees in Tehran, Iran. According to the purpose of the research, the judgmental sampling method has been used in this research. Although in this method, the generalization of findings may be limited, it is a suitable method for the statistical population with information. For this purpose, the data collection defines six face-to-face meetings by faculty members and electronic industry members. The existence of high-level education and the working of experts who had experience for more than six years make the questionnaire reliable. Seven experts shared their thoughts on the finalization of SSC, seven specialists on applying FCM, and four on employing HFLTS VIKOR. They were exposed to the ideas of Industry 4.0, supplier selection, the fundamentals of methods, and the fundamentals of surveys. This whole procedure takes two months. After meetings with the manager, other representatives of the company, and faculty members, based on the literature review and experts' opinions, appropriate criteria were selected to evaluate suppliers in industry 4.0. Table 3 illustrates key sub-criteria according to three criteria, economic, environmental, and social.

Fuzzy cognitive map

The FCM approach is implemented to determine the weight of each criterion. Seven experts expressed their opinions about the defined relationship between criteria. The average matrix based on the collected opinions of these seven experts is used to demonstrate the weights of the connections among nodes (shown in Table 4). The Mental Modeler software is used to implement the cause-effect diagram, which is illustrated in Fig. 5. According to Table 3, the sub-criteria are divided into three economic, social, and environmental categories. The economic criteria are shown in red, the social criteria in yellow, and the environmental criteria in blue in Fig. 5.

The nodes in this diagram can be divided into three categories. The first one is transmitter or driver nodes; these nodes are only affected by other nodes. According to Fig. 5, only the management awareness of intelligent technologies sub-criterion falls into this category. The second category is receiver nodes; these nodes are only affected by other nodes. Waste management by using smart technologies and collaboration, and digital communication are the sub-criteria that falls into the second category. Finally, the third category is ordinary nodes; these nodes simultaneously affect other nodes. Other sub-criteria are in this last category.

Each node has three characteristics: output degree, input degree, and centrality. Out-degree displays the summation weights of the node effects on other nodes. Moreover, In-degree is the absolute summation of weights that affected the node. Finally, centrality is calculated based on the summation of two in-degrees and out-degrees; all of them for each criterion are shown in Table 5.

Based on Table 5, technology capability has the highest output degree among the sub-criteria. Additionally, waste management by using smart technologies, collaboration, and digital communication are two sub-criteria, which their out-degree is zero and have the least influence. Furthermore, quality improvement by using smart technologies, collaboration, and digital communication, waste management by using smart technologies, and green and smart production are the most influenced sub-criteria, respectively. besides, the in-degree of the

Table 3 The criteria and sub-criteria for supplier selection

Criteria		Sub-criteria
Economic	C1	Technology capability
	C2	Flexibility by using smart technologies
	C3	Quality improvement by using smart technologies
	C4	Price reduction and cost using smart technologies
Environment	C5	Digital design in a digital way
	C6	Green and smart logistics
	C7	Green and smart production
	C8	Waste management by using smart technologies
Social	C9	Health and safety of employees in the digital workplace
	C10	Collaboration and digital communication
	C11	Data security in the digital space
	C12	Management awareness of smart technologies
	C13	Social activities to promote smart technologies

management awareness of smart technologies is zero, which means that other sub-criteria do not impact it. Centrality degree demonstrates the importance of a sub-criterion. The higher value for centrality shows a higher weight in sub-criteria (Gray et al. 2013). Thus, quality improvement by using smart technologies, and technology capability have the most centrality degree, respectively. For obtaining the weights of the sub-criteria, their centrality was normalized by the linear normalization method. The weights of sub-criteria obtained from the FCM method are introduced in Table 6.

HFLTS VIKOR

At this stage, the HFLTS VIKOR method is used to evaluate four suppliers specified by {X1, X2, X3, X4}. For this purpose, the company selected four decision-makers denoted by {R1, R2, R3, R4}. Decision-makers described the performance of each option against all sub-criteria based on using the comparative linguistic expression (Rodriguez et al. 2012). The linguistic expressions based on hesitant fuzzy linguistic decision matrices are displayed in Tables 7, 8, 9, and 10.

The VIKOR problem-solving is summarized as follows:

Table 4 Interactive matrix of average opinions of experts

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
C1			0.829		0.657	0.625				0.829	0.725		
C2	0.629			0.800			0.543						
C3		0.543		0.714			0.657	0.600					
C4			0.743										
C5		0.543				0.657	0.857	0.771					
C6											0.325		
C7			0.657					0.829					
C8													
C9			0.714										
C10													
C11										0.743			
C12	0.829												0.743
C13									0.686	0.771			

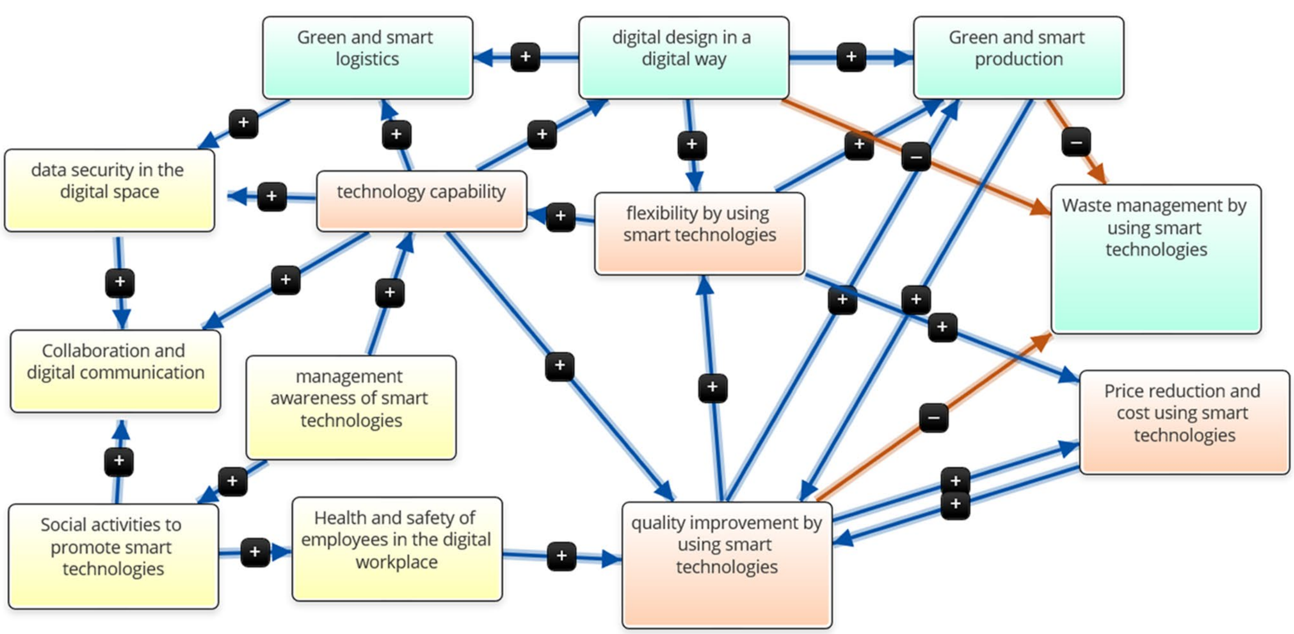

Fig. 5 Cause-effect diagram of 13 sub-criteria

- Step 1. Compute the normalized decision matrix.
- The linguistic term set considered for analysis is S = {S_0= very low; S_1 = low; S_2 = moderately low; S_3 = moderate; S_4 = moderately high; S_5 = high;S_6 = very high}. Also, all the sub-criteria are benefit attributes. Therefore, Tables 7, 8, 9, and 10 are the normalized fuzzy linguistic decision matrices.
- Step 2. Define the experts' importance weights.
- The weight vector of the experts λ = (0.25, 0.15, 0.22, and 0.38) is determined based on work experience, job position, and education.
- Step 3. Compute the group's hesitant fuzzy linguistic decision matrix.

The group hesitant fuzzy linguistic decision matrix is obtained by using the HFLWA operator.

The computation of r^c_{16} is an instance that the possibility distributions corresponding to $r^{(1)}_{16}$, $r^{(2)}_{16}$, $r^{(3)}_{16}$ and $r^{(4)}_{16}$ are:

$$P^{(1)}_{16} = (0, 0, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}, 0, 0)$$

$$P^{(2)}_{16} = (0, 0, 0, \frac{1}{2}, \frac{1}{2}, 0, 0)$$

$$P^{(3)}_{16} = (0, 0, 0, \frac{1}{3}, \frac{1}{3}, \frac{1}{3}, 0)$$

$$P^{(4)}_{16} = (0, 0, \frac{1}{2}, \frac{1}{2}, 0, 0, 0)$$

We have $P^c_{16} = (0, 0, 0.2733, 0.4217, 0.2317, 0.0733, 0)$ where the elements of P^c_{16} are obtained from (10). Other elements of R_c can be analogously calculated.

- Step 4. Define the worst f^-_j and the best f^+_j values.

Table 5 Input, output, and centrality degree of each sub-criterion

Code	Sub-criterion	Output degree	Input degree	Centrality
C1	Technology capability	3.68	1.46	5.14
C2	Flexibility by using smart technologies	1.97	1.08	3.05
C3	Quality improvement by using smart technologies	2.5	2.96	5.46
C4	Price reduction and cost using smart technologies	0.74	1.51	2.25
C5	Digital design in a digital way	2.82	0.66	3.48
C6	Green and smart logistics	0.33	1.28	1.61
C7	Green and smart production	1.51	2.06	3.57
C8	Waste management by using smart technologies	0	2.19	2.19
C9	Health and safety of employees in the digital workplace	0.71	0.68	1.39
C10	Collaboration and digital communication	0	2.34	2.34
C11	Data security in the digital space	0.74	1.06	1.8
C12	Management awareness of smart technologies	1.56	0.00	1.56
C13	Social activities to promote smart technologies	1.45	0.74	2.19

Table 6 The weights of sub-criteria obtained from the FCM method

Code	Sub-criteria	Weight (Wj)
C1	Technology capability	0.143
C2	Flexibility by using smart technologies	0.085
C3	Quality improvement by using smart technologies	0.152
C4	Price reduction and cost using smart technologies	0.062
C5	Digital design in a digital way	0.097
C6	Green and smart logistics	0.045
C7	Green and smart production	0.099
C8	Waste management by using smart technologies	0.061
C9	Health and safety of employees in the digital workplace	0.039
C10	Collaboration and digital communication	0.065
C11	Data security in the digital space	0.050
C12	Management awareness of smart technologies	0.043
C13	Social activities to promote smart technologies	0.061

Table 7 Hesitant fuzzy linguistic decision matrix R 1

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
X1	$\{s_4,s_5\}$	$\{s_2,s_3\}$	$\{s_5\}$	$\{s_1,s_2\}$	$\{s_3,s_4\}$	$\{s_2,s_3,s_4\}$	$\{s_3\}$	$\{s_4,s_5\}$	$\{s_2,s_3,s_4\}$	$\{s_5,s_6\}$	$\{s_6\}$	$\{s_4,s_5\}$	$\{s_3,s_4\}$
X2	$\{s_2,s_3\}$	$\{s_4\}$	$\{s_2,s_3\}$	$\{s_4,s_5\}$	$\{s_1\}$	$\{s_1\}$	$\{s_1\}$	$\{s_0,s_1,s_2\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_3,s_4,s_5\}$	$\{s_2,s_3,s_4\}$	$\{s_0\}$
X3	$\{s_4,s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_2,s_3\}$	$\{s_0,s_1,s_2\}$	$\{s_1,s_2\}$	$\{s_1,s_2,s_3\}$	$\{s_1,s_2\}$	$\{s_2,s_3,s_4\}$	$\{s_3,s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_0,s_1,s_2\}$	$\{s_0\}$
X4	$\{s_4\}$	$\{s_3,s_4\}$	$\{s_4\}$	$\{s_3\}$	$\{s_2,s_3\}$	$\{s_2,s_3\}$	$\{s_3,s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_3,s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_5,s_6\}$	$\{s_2,s_3\}$

Table 8 Hesitant fuzzy linguistic decision matrix R 2

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
X1	$\{s_4,s_5\}$	$\{s_5\}$	$\{s_5,s_6\}$	$\{s_1,s_2\}$	$\{s_2,s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_4\}$	$\{s_2,s_3\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_4\}$	$\{s_3\}$
X2	$\{s_3\}$	$\{s_3,s_4\}$	$\{s_2,s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_1\}$	$\{s_1,s_2,s_3\}$	$\{s_2\}$	$\{s_1,s_2\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_2\}$	$\{s_1\}$
X3	$\{s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_2,s_3\}$	$\{s_1,s_2\}$	$\{s_1,s_2\}$	$\{s_2,s_3\}$	$\{s_1,s_2\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_1\}$	$\{s_0,s_1\}$
X4	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_3,s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_2,s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_2,s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_3,s_4\}$	$\{s_2,s_3\}$

Table 9 Hesitant fuzzy linguistic decision matrix R 3

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
X1	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_1,s_2,s_3\}$	$\{s_2,s_3\}$	$\{s_3,s_4,s_5\}$	$\{s_2,s_3\}$	$\{s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_4,s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_2,s_3\}$
X2	$\{s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_3\}$	$\{s_5,s_6\}$	$\{s_1,s_2\}$	$\{s_1,s_2\}$	$\{s_2,s_3\}$	$\{s_1,s_2\}$	$\{s_2,s_3\}$	$\{s_3,s_4,s_5\}$	$\{s_5\}$	$\{s_3,s_4\}$	$\{s_0,s_1\}$
X3	$\{s_3,s_4\}$	$\{s_4,s_5,s_6\}$	$\{s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_2,s_3\}$	$\{s_2,s_3\}$	$\{s_1,s_2\}$	$\{s_1\}$	$\{s_4\}$	$\{s_4,s_5\}$	$\{s_4,s_5,s_6\}$	$\{s_2,s_3\}$	$\{s_1\}$
X4	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_2,s_3\}$	$\{s_2,s_3,s_4\}$	$\{s_4\}$	$\{s_4,s_5\}$	$\{s_4\}$	$\{s_5\}$	$\{s_5\}$	$\{s_3,s_4,s_5\}$	$\{s_5\}$	$\{s_1,s_2\}$

Table 10 Hesitant fuzzy linguistic decision matrix R 4

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
X1	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_4,s_5,s_6\}$	$\{s_2,s_3\}$	$\{s_2,s_3,s_4\}$	$\{s_2,s_3\}$	$\{s_3\}$	$\{s_3,s_4\}$	$\{s_1,s_2,s_3\}$	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_3,s_4,s_5\}$	$\{s_0,s_1,s_2\}$
X2	$\{s_2,s_3\}$	$\{s_3,s_4\}$	$\{s_2,s_3\}$	$\{s_4,s_5\}$	$\{s_1,s_2,s_3\}$	$\{s_1,s_2,s_3\}$	$\{s_1,s_2\}$	$\{s_2,s_3\}$	$\{s_3,s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_3,s_4,s_5\}$	$\{s_3,s_4\}$	$\{s_0,s_1\}$
X3	$\{s_3\}$	$\{s_2,s_3,s_4\}$	$\{s_3,s_4\}$	$\{s_2,s_3,s_4\}$	$\{s_1,s_2\}$	$\{s_1,s_2,s_3\}$	$\{s_1,s_2,s_3\}$	$\{s_0,s_1,s_2,s_3\}$	$\{s_2,s_3,s_4\}$	$\{s_3,s_4,s_5\}$	$\{s_2,s_3\}$	$\{s_2,s_3,s_4\}$	$\{s_0,s_1,s_2\}$
X4	$\{s_4\}$	$\{s_3,s_4,s_5\}$	$\{s_5\}$	$\{s_4\}$	$\{s_2,s_3,s_4,s_5\}$	$\{s_3,s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_3,s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_3,s_4\}$	$\{s_2,s_3\}$

The best and the worst values for each criterion are obtained by applying the relative ideal solutions by Eq. (11) and Eq. (12). These values are depicted in Table 11.

- Step 5. Compute the S_i and R_i values**.**

Based on the ideal relative solutions, the values of Si and Ri are computed by using Eq. (14) and Eq. (15), respectively. It should be noted that w_j in these equations is the weight vector obtained in Table 6.

- Step 6. Calculate the Q_i values.

After calculating the values of S_i and R_i to prioritize the alternatives, the value of Q_i is calculated through Eq. (17). Table 12 illustrates S_i, R_i, and Q_i when setting v = 0.5.

- Step 7. Rank the alternatives.

The ranking was based on sorting S_i, R_i, and Q_i values in descending order (Table 12), so the best options are based on the lowest values of X_Q, X_S, and X_R.

- Step 8. Compromise solution.

As a result, due to Eq. (18), *Cond*$_1$ is being met. Also, due to A_4 being chosen as the best rated by X_S, and X_R, the *Cond*$_2$ is being met. Hence, as both *Cond*$_1$ and *Cond*$_2$ are accepted, only the A_4 is selected as the best supplier.

The obtained results are collected using the criteria weights determined by the FCM. To analyze the stability of results regarding changes in criteria weights, a sensitivity analysis is performed by implying changes in the criteria' importance. Since the weights are normalized, i.e., their sum is equal to 1, to analyze the effect of increasing or decreasing the weight of criterion j by Δ%, the new weights of criteria are calculated as follows.

$$w'_j = (1 + \Delta)w_j \tag{19}$$

$$w'_k = w_k - \frac{\Delta w_j}{n-1} \forall k \neq j \tag{20}$$

Figure 6 illustrates the sensitivity analysis results. The criteria are placed on the horizontal axis from the most to the least sensitive ones, respectively. The vertical axis shows the value of change in criteria weights, i.e., Δ, that caused a change in the ranking result. For each criterion, the value Δ gradually increased/decreased until the first change occurred in the results or one of the other criteria weights became negative. The corresponding Δ and the new solutions are colored. First, for $-1 \leq \Delta < 0$, no change is determined in the result. The results are insensitive regarding criteria weights decrease. For $\Delta > 0$, let us examine the effect of changes on W_2. According to the figure, a value of 55.05% is reported. This means that the obtained solution is not sensitive to the changes on W_2 in the range of $0 < \Delta < 0.5505$, i.e., when $0.08381 < W_{15} < 0.1294$. For $\Delta > 0.5505$, the ranking is changed to $A_1 > A_4 > A_3 > A_2$.

According to Fig. 6, three different results are obtained for changes in criteria weights. The most sensitive criteria seem to be W_2 with $\Delta = 55.05\%$. Next, for W_3 with $\Delta = 84.5\%$, the result is changed to $A_1 > A_4 > A_3 > A_2$. Next, for W_4 with $\Delta = 203\%$ and W_9 with $\Delta = 317\%$, the result is changed to $A_4 > A_3 > A_1 > A_2$. Finally, for W_8 with $\Delta = 246\%$, W_{11} with $\Delta = 225\%$, and W_{11} with $\Delta = 282\%$, the result is changed to $A_4 > A_1 > A_2 > A_1$. Considering the obtained results, the results didn't show sensitivity to changes in W_1, $W5$, W_6, W_7, W_{10}, and W_{11}. Considering the results of sensitivity analysis, the results illustrated great stability regarding the changes in criteria weights. Also, the first and second-ranked alternatives, i.e., A_4 and A_1 remained the same in the different results.

Table 11 The best f_j^+ and the worst f_j^- values by using the relative ideal solution

Criteria	f_j^+	f_j^-	Criteria	f_j^+	f_j^-
C_1	r_{41}^c	r_{21}^c	C_8	r_{48}^c	r_{38}^c
C_2	r_{12}^c	r_{22}^c	C_9	r_{49}^c	r_{19}^c
C_3	r_{13}^c	r_{23}^c	C_{10}	r_{410}^c	r_{210}^c
C_4	r_{24}^c	r_{14}^c	C_{11}	r_{111}^c	r_{311}^c
C_5	r_{45}^c	r_{25}^c	C_{12}	r_{412}^c	r_{312}^c
C_6	r_{46}^c	r_{26}^c	C_{13}	r_{113}^c	r_{213}^c
C_7	r_{47}^c	r_{27}^c			

Conclusion

The emergence of developing technologies leads companies to use competitive strategies to survive and grow in the global market. The advent of industry 4.0 technologies makes firms adopt their performances with this revolution. One of the most important effects of a new generation is SCM. Supply chains must change to adopt industry 4.0 to enhance the overall performance of companies. Digitalization leads to reducing costs and risks and improving efficient SCM. Hence, firms pay penchant to work with digital suppliers. The main goal of this research activity is to highlight the process of SS by using the FCM method for weighting criteria and then using HFLTS VIKOR to rank and select suitable suppliers. This research has determined three criteria, social, environmental, and economic, and 13 sub-criteria based on the 4th generation revolution. Categorizing sub-criteria in these three criteria has received more attention in recent years. These three categories are considered agility based on previous studies (Ghadimi et al. 2019; Mohammed et al. 2018). However, by reviewing the literature, some studies did not include agility in their research but used these three categories (Çalık, 2021). Quality improvement by using smart technologies ($C3$), technology capability ($C1$), and green and smart production ($C7$) are the mainstay of sub-criteria, which have the highest weight by 0.152, 0142, and 0.099, respectively. Also, quality improvement by using smart technologies (C3) is used as the most impressive criterion by 3.68 output degree, and technology capability (C1) is introduced as the most effective one by 2.96 input degree. As a result, supplier4, supplier1, supplier3, and supplier2 are chosen severally as suitable suppliers for the mentioned firm. The developed methodology for solving the SS 4.0 problem can aid companies in implementing an integrated framework to prioritize and choose suitable suppliers. The sensitivity analysis performed on the criteria weights also shows the stability of the obtained results which increases the trustiness of the results.

Table 12 The S_i, R_i, and Q_i rankings and the compromise solution of alternatives by VIKOR method (for $v = 0.5$)

	A_1	A_2	A_3	A_4	Ranking	Compromise solution
S_i	0.2115	0.8709	0.7472	0.1084	$A_4 \succ A_1 \succ A_3 \succ A_2$	A_4
R_i	0.0620	0.1520	0.0970	0.0438	$A_4 \succ A_1 \succ A_3 \succ A_2$	A_4
Q_i	0.1518	1	06,648	0	$A_4 \succ A_1 \succ A_3 \succ A_2$	A_4

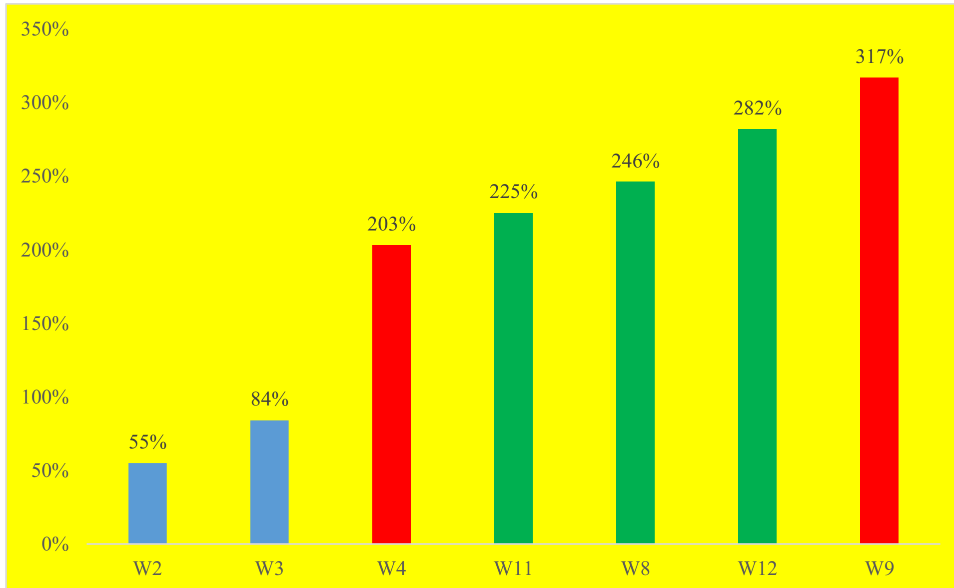

Fig. 6 Sensitivity analysis of the results

This research contributes to identifying a set of SSC in the 4th generation revolution by using a literature review and fuzzy cognitive map method, which is one of the new issues of SS in the intelligent era. As in the fourth revolution era, some issues, including technology and the environment, have great importance and have many changes over time. A method should be used that responds to these ambiguities and uncertainties. As a result, the problem is modeled as an MCDM problem and is solved via the VIKOR method, which is developed into the HFLTS VIFOR method so that the experts can have more freedom of expression.

The presented model provides managerial insights for managers such as SS and electronics SC under industry 4.0. Regarding the infrastructure of industry 4.0 is improving daily worldwide, managers need to know more about the crucial criteria in this era. The presented model provides some essential criteria for SS 4.0. The relations between criteria in this era are one of the issues that this paper has focused on. In other words, if managers know more about the criteria relationships, they can focus more on the most important criteria, which have more impact on others, and make better decisions. The fuzzy cognitive map helps managers to provide an obvious vision for this aim. For instance, quality improvement by using smart technology ($C3$) has the highest weight by having the highest summation of all relations, among other criteria. Therefore, to gain the highest quality, managers should enhance the technology capability ($C1$), price reduction and cost using smart technologies ($C4$), green and smart production ($C7$), and health and safety of employees in the digital workplace ($C9$), which have relations with it. Besides, three aspects of social, environmental, and economic are considered in this paper. Managers may comprehend the significance of each criterion by applying the findings of this article. As a result, they may concentrate more on the criterion with the greatest importance.

Some limitations in the industry are tangible, especially for underdeveloped and developing countries, which have no suitable facilities to transmit to the new generation. Countries must provide convenient infrastructures based on industry 4.0. On the other hand, factory capacity limitation is one of the inevitable issues which needs to be an order allocation subject. In the future, researchers can pay attention to this issue in industry 4.0 by considering uncertainty in data. Also, one of the criticisms of using the MCDM method is the existence of a variety of them, which means it is possible to have different results. Therefore, using a variety of them by considering the suitable combined method can be used in the future.

Author contribution Asana Hosseini Dolatabad: conceptualization, methodology, software, writing—original draft preparation. Jalil Heidary Dahooie: data curation. Jurgita Antucheviciene: writing—reviewing and editing, supervision. Mostafa Azari: supervision, methodology, software, validation. Seyed Hossein Razavi Hajiagha: visualization, investigation.

Data availability Data will be made available on request.

Declarations

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