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A Comprehensive Evaluation Model for Smart Supply Chain Based on The Hybrid Multi-Criteria Decision-Making Method

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ABSTRACT

Enhancing the smartness of the supply chain under the influence of information technology development at different levels can have a significant effect on its overall performance and a favorable response to the continuous changes in the business environment in the wide network of local and global supply chains. Therefore, in this study, the important and influential aspects of supply chain smartness have been investigated via a comprehensive assessment model. Then, evaluation criteria are prioritized using the new combined multi-criteria decision-making method. For this purpose, the supply chain of Iran Khodro Company has been considered as a case study. The identification and selection of assessment criteria are based on the literature review and experts' opinions via the Delphi method. Then, by using the developed best-worst group fuzzy method, the final prioritization of the criteria has been proposed. Finally, the evaluation of smartness improvement solutions is proposed by using the Vikor method. The main obtained results indicate the importance of cost, technology, security, customer relationship management, and agility criteria.

1. Introduction

Information technology has revolutionized the industry and can provide a basis for applying it to optimize supply chain management. Under the influence of the intensifying competitive environment in supply chain management, we are witnessing the increasing efforts by organizations to enhance the efficiency and performance of the supply chain. The advancing progress of information technology has transformed the industry and can serve as the foundation for its application in improving supply chain management. The world has experienced three industrial revolutions in the past. The fourth industrial revolution can be defined by various new technologies. This revolution integrates the physical, digital, and biological realms and will impact all fields. New technologies like nanotechnology, the Internet of Things (IOT), and 3D printing are key technologies that fuel this new industrial revolution and will fundamentally change the

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functioning of the modern economy and affect the level of employment, the form of jobs, the nature of work and business operating models [1].

In the meantime, supply chain management has undergone extensive changes under the influence of emerging electronic technologies such as cloud production, 3D printing, and the Internet of Things. Companies are moving away from supply chains dependent on prediction and reaction and are transitioning towards becoming more intelligent. Therefore, we are witnessing a shift from competition among organizations to competition among supply chains [2]. In traditional supply chains, there were few products and low productivity, high-risk working conditions, high production costs, and a long time for the product to enter the market. However, in smart supply chains, there is higher output and productivity, higher quality products, a safer work environment, less waste, lower production costs, and a faster time to market [3].

The rapid growth of technology and the increasing focus on the ever-changing digital world of information technology pose challenges for senior management in organizations. There is often a lack of knowledge and understanding among senior management regarding the broader aspects of information technology systems. This leads to difficulties in properly evaluating information technology initiatives and ensuring their alignment with strategic goals. To successfully manage and evaluate performance, organizations require a capable system. Therefore, the establishment of a measurement and evaluation system is essential to achieve effective and stable management [4].

The development of an intelligent supply chain management system can lead to improvement of the performance of the resulting system compared to traditional systems, the effects of which can transform industries and businesses by clarifying businesses and making processes intelligent on a large scale, and small and large economic enterprises by reducing costs. and improve performance. Since supply chain management is a subject that is rapidly developing as an interdisciplinary concept that includes the range of marketing, procurement, organizational behavior, and economics, it is composed of different circles and different factors that affect the chain [5]. Therefore, in this study, the factors affecting supply chain smartness have been evaluated, some of the most important of which are:

- Cost factor: Many organizations have concluded that cost reduction plays an effective role in profitability and competitive advantage. One of today's companies' primary concerns is the optimal use of organizational resources. Having a "cost reduction strategy," or in other words, rational management of costs, can be effective in the optimal use of available resources. It can be claimed that cost reduction is not only a threat but also an opportunity; it identifies and utilizes the unused capacities of an organization [6].
- Technology factor: To effectively address the risks inherent in the decision-making environment and achieve business goals, the supply chain needs to be intelligent; Fortunately, new technologies, precision tools, and smart connections in the supply chain can create a stable and secure supply chain that businesses require today [7]. Adopting the right technology in the supply chain helps the organization perform better against competitors and increase productivity.
- Agility factor: supply chain agility is recognized as one of the pivotal aspects in modern supply chain management [8]. It empowers an organization to promptly and efficiently react to market shifts and other uncertainties This capability, in turn, enables the organization to establish a competitive edge. Hence, the essentiality and significance of supply chain agility, stemming from the urgency for swift responsiveness, meeting customer demands, adapting to the continuously evolving market landscape, and similar

circumstances prevalent across numerous industries, are evident both theoretically and empirically.

- Customer relationship management factor: Numerous variables contribute to the successful performance of the supply chain, but in today's business landscape, one of the most crucial factors is the ability of the Customer Relationship Management (CRM) system to identify and meet customer needs and demands. The contemporary challenge lies in how organizations comprehend the specific requirements of their customers, ensuring their satisfaction while simultaneously managing costs and elevating quality. The avenue for implementing this notion is through the adapting of a robust customer relationship management system [9].
- Security Factor: The three key flows of materials, information, and money in supply chain management will be examined in a coordinated manner. Today's supply chains often deal with computer networks and are evolving into intelligent supply chains. Meanwhile, cyber-attacks seriously threaten the smart networks of the supply chain. Security is very important for the supply chain and the companies in this chain, which must always be maintained along the entire length of the chain [3-4].

Therefore, in this study, an attempt has been made with a comprehensive and integrated perspective to develop an evaluation model that encompasses a set of both quantitative and qualitative factors, in contrast to the existing models, addressing crucial issues in the Fourth Industrial Revolution pertaining to intelligent supply chains. Additionally, recognizing the presence of uncertainty in the evaluation domain, a combination of modern methods involving quantitative assessment and analyzable qualitative indicators has been employed to formulate a comprehensive model for assessing supply chain smartness. To this end, initially, utilizing the Delphi method, experts' opinions on the criteria and sub-criteria were collected. Subsequently, a researcher-designed questionnaire was distributed to gather experts' assessments on the significance of influential indicators in supply chain intelligence. Uncertainty has been accounted for in the evaluation process by applying the fuzzy programming approach. Furthermore, employing the best-worst multi-criteria decision-making technique for pairwise comparisons concerning the criteria, and utilizing the VIKOR technique to prioritize the sub-criteria within each criterion. The supply chain of Iran Khodro Company has been scrutinized as a case study. The rationale for selecting the automotive supply chain stems from its substantial impact on economic growth compared to other sectors. Moreover, statistics indicate that the automotive industry has contributed 21% to added value creation and 4% to the Gross Domestic Product (GDP)in recent years, solidifying its position as a driving force within the nation's industrial landscape.

1.1 Literature Review

In this section, studies conducted in the field of supply chain intelligence have been reviewed in terms of evaluation criteria and analysis techniques. Akhtar [10]. defines the supply chain based on Industry 4.0 as a modern system with interconnected processes that each execute distinct programs but are in a comprehensive and extensive relationship, leading to the creation of integration and efficiency at all chain levels. Liu *et al.,* [11] have examined the significance of big data technology in supply chain management and have concluded that selecting the appropriate big data technology should be contingent upon the company's internal and external environment. Also, Aliahmadi *et al.,* [12] in their research, have tried to study and analyze the key indicators based on artificial intelligence and Internet of Things technology in the sustainable supply chain. The literature review shows that investing in this Technology is indispensable to achieving sustainable benefits. Also, the use of this technology, due to networking and the existence of the Internet, requires appropriate security solutions for information technology, the workforce with the required skill set, and information sharing in an integrated environment with business partners. Marinagi *et al.,* [13] focused on the impact of Industry 4.0 technologies on key performance indicators in a flexible supply chain. They also examined how each technology in Industry 4.0 affects the most important elements of the supply chain.

Zhang *et al.,* [14] argue that the rise of self-driving vehicles and the emergence of alternative energy sources for them have amplified the demand for the advancement of intelligent logistics systems in the contemporary world. In their article, they scrutinize the influence of artificial intelligence based on block chain transactions and conclude that this contributes to enhancing operations in the automotive supply chain. Manavalan and Jayakrishna [15] have discussed and provided criteria that companies can use to assess their readiness for entering Industry 4.0. Szozda [16] views industry-based supply chain management as a shift from conventional relationships among chain levels towards a network of data connections and the integration of technologies in chain systems and components. Dalasega *et al.,* [17] analyzed the interview data using thematic analysis and identified agility, current situation, digitization, connectivity and networking, monitoring, employee culture, security, user-friendliness, and transportation as crucial factors. They further emphasized that these factors are significant in the industry. Ma *et al.,* [18] presented an integrated model for time and cost competition with heterogeneous customers and introduced the concept of a time-based supply chain. Silva *et al.,* [19] in a review study introduced widely used technologies in industry 4.0. Afshari *et al.,* [20] conducted an investigation into various technologies in the supply chain and concluded that the integration of these advanced technologies in supply chain management results in enhanced factory workflow, improved material tracking, and optimized distribution, ultimately maximizing operational income. Petroudi *et al.,* [21] have introduced a comprehensive framework for analyzing challenges in the supply chain management of human resources within the Red Crescent population of Iran, employing the Delphi technique. Some previous studies have been examined in Table 1.

Table 1
Previous and current studies in the field of criteria affecting supply chain intelligence

Study	**Criteria**				
	Cost	**Agility**	**Technology**	**Security**	**Customer relation management**
Nozari and Edalatpanah [22]				✓	
Sharma and Dash [23]					✓
Dallasega *et al*. [17]		✓		✓	
Ma *et al*., [18]	✓	✓			
Wu [24]		✓			
Ditizio and Smith [25]					✓
Current study	✓	✓	✓	✓	✓

The review of the subject literature and the results of the conducted studies indicate that despite the developments made in the evaluation models in the smart supply chain, due to the complexity of the subject under evaluation and the influence of different and diverse factors under different decision-making spaces, it still requires further development. The mentioned models will be based on expanding the scope of the updated criteria according to the change in the expectations of the relevant stakeholders in terms of measurement tools and how to analyze the results (Table 1). Currently, despite the importance of the issue, there are a limited number of studies on the intelligent supply chain, and the need to develop evaluation models is still felt. In this study, after studying the influencing factors on supply chain smartness, the desired factors have been identified, reviewed, and prioritized according to the experts' opinions.

2. Methodology

The current study is a theoretical-applied research conducted at the Iran Khodro site. The aim of this research is to assess and prioritize key criteria for enhancing supply chain intelligence, along with the sub-criteria for each component. Experts in production, information technology, and after-sales services within the organization were chosen as research participants. Following the research model implemented, this study endeavors to identify the dimensions and factors outlined in Lin's model [26] as the primary criteria. Subsequently, this set of dimensions and factors was updated based on the expert opinions gathered through the Delphi technique. Following this, through the analysis of data obtained from a paired comparisons questionnaire, and utilizing the fuzzy best-worst group technique, each criterion was evaluated, allowing for the determination of the most and least crucial criteria [27-30]. The stages of research implementation are illustrated in Figure 1.

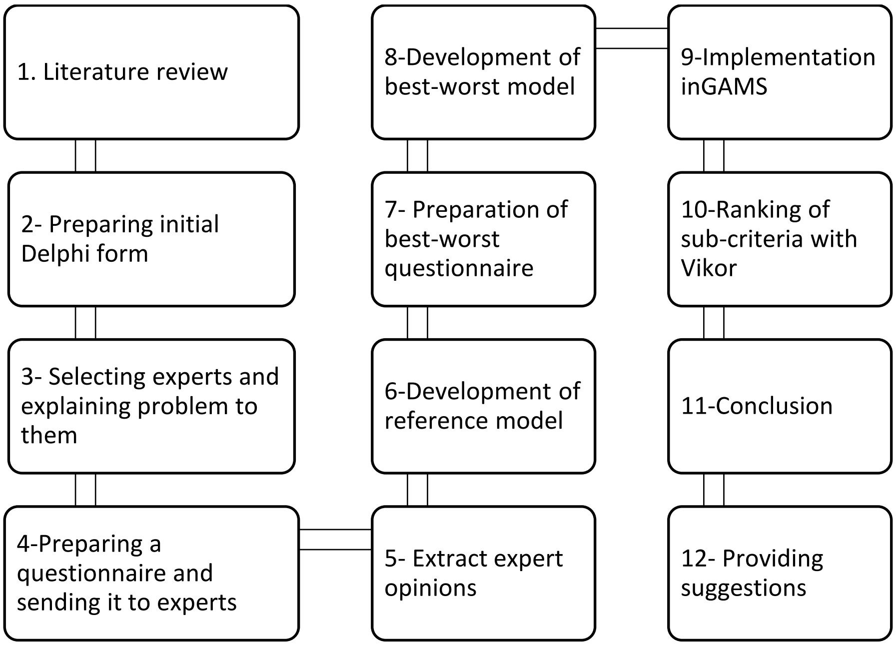

Figure 1. Research method steps

The criteria were selected based on findings from the literature on intelligent supply chains. initially, the literature related to this field was reviewed and the important factors and models that can make the supply chain smarter were collected from multiple sources. In this study, to collect the necessary data after reading the literature and library studies, the opinions of industry experts have been examined. The classification obtained from both research literature and experts' opinions was refined using the Delphi technique. Experts were provided with a questionnaire to assess the importance of each factor in the model, using a scale ranging from 1 (low importance) to 9 (high importance). They were also given the opportunity to introduce any additional relevant factors and indicate their associated importance levels The Best-Worst Fuzzy method was then applied to assign weights to each criterion. Finally, the sub-criteria were prioritized using the Vikor technique (see Figure 1).

3. Results

Table 2 displays the five performance evaluation criteria for the intelligent supply chain, which were identified and validated by experts through the Delphi method. The panel of experts was drawn from employees of the Iran Khodro site, possessing pertinent academic background and over five years of professional experience in the automotive industry.

Table 2
Evaluation indicators of supply chain intelligence

Label	**Evaluation criteria**
C_{11}	Cost
C_{21}	Agility
C_{31}	Security
C_{41}	Technology
C_{51}	Customer relationship management

Table 3 presents the pairwise comparisons made by experts regarding the dimensions of supply chain intelligence. In each expert's evaluation, the first row of the table indicates their preference for the best index over all other indicators, while the second row reflects their preference for all indicators over the least favorable index.

Table 3
Pairwise comparisons of experts about the criteria affecting supply chain intelligence

DM	Best Criteria	Worst Criteria	Input Criteria				
			COST	Agility	Security	Technology	Customer Relationship Management
1	C_{41}	----------	(5.2,2,3.2)	(11.2,5,9.2)	(7.2,3,5.2)	(1,1,1)	(9.2,4 ,7.2)
	----------	C_{21}	(11.2,5,9.2)	(1,1,1)	(7.2,3,5.2)	(9.2,4,7.2)	(5.2,2,3.2)
2	C_{31}	----------	(5.2,2,3.2)	(9.2,4,7.2)	(1,1,1)	(5.2,2,3.2)	(7.2,3,5.2)
	----------	C_{51}	(11.2,5,9.2)	(5.2,2,3.2)	(7.2,3,5.2)	(9.2,4,7.2)	(1,1,1)
3	C_{11}	----------	(1,1,1)	(11.2,5,9.2)	(7.2,3,5.2)	(5.2,2,3.2)	(9.2,4,7.2)
	----------	C_{21}	(11.2,5.9.2)	(1,1,1)	(9.2,4,7.2)	(9.2,4,7.2)	(7.2,3,5.2)

As mentioned, the best-worst group fuzzy method was employed to derive fuzzy weights for determining the most and least influential factors. This model was encoded and solved using Lingo optimization software. Subsequently, the experts' assessments of the indicators were gathered. After evaluating each expert's opinions using the best-worst group fuzzy method in Lingo software,

the resulting weights were averaged. Ultimately, the definitive weights for each dimension of intelligence were determined based on their priority, as outlined in Table 5. Below is the continuation of the mathematical model employed in the research:
In this study, the Fuzzy Best-Worst method was devised for group decision-making, incorporating the perspectives of three experts to select and assign weights to indicators. The steps of this method are outlined as follows:

Step 1: Determining the decision-making criteria: In this initial stage, experts define the necessary indicators for decision-making as $\{c_1. c_2 \dots c_n\}$.

Step 2: Experts identify the best (most important, most desirable) and worst (least important, least desirable) indicators without making any direct comparisons at this stage.

Step 3: In this phase, experts express their preference for the best index over the other indices using triangular fuzzy numbers, as presented in Table 4. These preferences are represented in the form of $\tilde{A}_B = (\tilde{a}_{B1}. \tilde{a}_{B2}. \dots . \tilde{a}_{Bn}$, where $\tilde{a}_{Bj}$ signifies the degree of preference for the best index over the jth index. Additionally,$\tilde{a}_{BB}$= (1,1,1) is established to denote the absolute preference of the best index over itself (refer to Table 4).

Table 4
Converting linguistic terms to fuzzy numbers

Membership function	Linguistic variables
(1,1,1)	Equal Importance (EI)
(0.6,1,1.5)	Weak Importance (WI)
(1.5,2,2.5)	Relatively Important (RI)
(2.5,3,3.5)	Very Important (VI)
(3.5,4,4.5)	Absolutely Important (AI)

Step 4: During this stage, experts establish their preference for all indicators in comparison to the worst indicator chosen in Step 2. This is achieved using the fuzzy numbers provided in Table 4, expressed as $\tilde{A}_w = (\tilde{a}_{1w}. \tilde{a}_{2w} \dots . \tilde{a}_{nw})$ signifies the degree of preference for the best index over the worst index, denoted as w, and $\tilde{a}_{ww}$=(1,1,1).
Step 5: Attaining the optimal weights for the indices $(\widetilde{w}_1^*. \widetilde{w}_2^*. \dots . \widetilde{w}_n^*)$: To determine the optimal weight for each index, pairs of $\frac{w_B}{w_j} - a_{Bj}$ and $\frac{w_j}{w_w} - a_{jw}$ are constructed. Ensuring these conditions hold true for all js, a solution is sought such that the expressions $\left|\frac{\bar{w}_B}{\bar{w}_j} - \bar{a}_{Bj}\right|$ and $\left|\frac{\bar{w}_j}{\bar{w}_w} - \bar{a}_{jw}\right|$ are maximized for all *j* , which are subsequently minimized. Taking into account the non-negativity and summation constraints of the weights, the model can be represented as the model (1):

$$\text{minmax}\{\left|\frac{\bar{w}_B}{\bar{w}_j} - \bar{a}_{Bj}\right| . \left\{\left|\frac{\bar{w}_j}{\bar{w}_w} - \bar{a}_j w\right|\right\} \qquad (1)$$

s.t.

$$\sum_j \bar{w}_j = 1$$

$$\bar{w}_j \geq 0. for\ all\ j$$

The above model can also be written as model (2):

$$\text{Min}\xi$$

s.t.

$$\left|\frac{\bar{w}_B}{\bar{w}_j} - \bar{a}_{Bj}\right| \leq \xi. for\ all\ j$$

$$\left|\frac{\bar{w}_j}{\bar{w}_w} - \bar{a}_{j_w}\right| \leq \xi. for\ all\ j \tag{2}$$

$$\sum_j \bar{w}_j = 1$$

$$\bar{w}_j \geq 0. for\ all\ j$$

If $\widetilde{w}_w = (l_w^w.m_B^w.u_w^w).\widetilde{w}_j = \left(l_j^w.m_j^w.u_j^w\right).\widetilde{w}_B = (l_b^w.m_b^w.u_b^w)$ respectively, the fuzzy weight of the best option is the jth option and the worst option, and $\tilde{a}_{Bj} = \left(l_{Bj}.m_{Bj}.u_{Bj}\right)$ is the preference of the best option over the jth option, $\tilde{a}_{jw} = (l_{jw}.m_{jw}.u_{jw})$ is the preference of the jth option to be the worst option and $\tilde{\xi}^* = (k^*.k^*.k^*)$, model (2) can be rewritten as model (3).

$$\text{min}\bar{\xi}^*$$

$$\left|\frac{(l_B^w.m_B^w.u_B^w)}{(l_j^w.m_j^w.u_j^w)} - \left(l_{Bj}.m_{Bj}.u_{Bj}\right)\right| \leq (k^*.k^*.k^*)$$

$$\left|\frac{(l_j^w.m_j^w.u_j^w)}{(l_W^w.m_W^w.u_W^w)} - \left(l_{jW}.m_{jW}.u_{jW}\right)\right| \leq (k^*.k^*.k^*)$$

$$\sum_{i=1}^{n} R\left(\bar{w}j\right) = 1 \tag{3}$$

$$l_j^w \leq m_j^w \leq u_j^w$$

$$l_j^w \geq 0$$

$$j = 1.2. \dots . n$$

Step 6: The weights derived from the model are de-fuzzified to yield a single weight for making decisions regarding the selection of indicators. If $a_i = (l_i . m_i . u_i)$, equation (4) from Table 5 can be utilized for de-fuzzifying the triangular fuzzy number.

$$R\left(\bar{a_i}\right) = \frac{l_i + 4m_i + u_i}{6} \quad (4)$$

Table 5
Final weights of supply chain smartness criteria

	Criteria	Fuzzy weight	Defuzzy weight	Rank
1	Cost	(0.738, 0.244, 0.244)	0.326	**1**
2	Agility	(0.126, 0.054, 0.039)	0.063	5
3	Security	(0.456, 0.193, 0.181)	0.234	**3**
4	Technology	(0.595, 0.210, 0.21)	0.274	**2**
5	Customer relationship management	(0.204, 0.078, 0.076)	0.098	4

In this study, according to the existence of experts, the best-worst combination method has been used, that is, both fuzzy and group methods have been combined for the first time in this study, which is shown below (Relation 5). The symbol k in this model represents the number of experts. Based on the best-worst base technique, experts determine the set criteria and determine the worst and the best criteria. After that, each expert declares the preference and importance of the best criteria over other criteria (using a number between 1 and 9). and in the same way declares the preferences for all the criteria compared to the worst criterion. In the next step, the optimal weights are obtained by solving the mathematical model. Finally, the final weight of each option or criterion is determined by each expert.

$$Min\ \lambda^*$$

$$\lambda \geq w'_k \lambda_k \ \ . \forall k$$

$$w_B^l - a_{Bj}^l w_j^u \leq \lambda_k w_j^u \ . \forall j . \forall k$$

$$w_B^l - a_{Bj}^l w_j^u \geq -\lambda_k w_j^u \ . \forall j . \forall k$$

$$w_B^m - a_{Bj}^m w_j^m \leq \lambda_k w_j^m \ . \forall j . \forall k$$

$$w_B^m - a_{Bj}^m w_j^m \geq -\lambda_k w_j^m \ . \forall j . \forall k \quad (5)$$

$$w_B^u - a_{Bj}^u w_j^l \leq \lambda_k w_j^l \ . \forall j . \forall k$$

$$w_B^u - a_{Bj}^u w_j^l \geq -\lambda_k w_j^l \ . \forall j . \forall k$$

$$w_j^l - a_{jW}^l w_W^u \leq \lambda_k w_W^u \ . \forall j . \forall k$$

$$w_j^l - a_{jW}^l w_W^u \geq -\lambda_k w_W^u \ . \forall j . \forall k$$

$$w_j^m - a_{jW}^m w_W^m \leq \lambda_k w_W^m \ .\forall j.\forall k$$

$$w_j^m - a_{jW}^m w_W^m \geq -\lambda_k w_W^m \ .\forall j.\forall k$$

$$w_j^u - a_{jW}^u w_W^l \leq \lambda_k w_W^l \ .\forall j.\forall k$$

$$w_j^u - a_{jW}^u w_W^l \geq -\lambda_k w_W^l \ .\forall j.\forall k$$

$$\sum_j R(\widetilde{w}_j) = 1$$

$$w_j^l \leq w_j^m \leq w_j^u$$

$$w_j^l \geq 0$$

In the subsequent discussion, the prioritization of sub-criteria will be addressed using the fuzzy Vikor method. Table 6 and Figure 2 present the outcomes pertaining to the data analysis of the cost sub-criterion. As depicted in the table, the results in this section illustrate that the cost sub-criterion exhibits Vikor indicators with values assigned as follows: installation cost (0), platform cost (0.156), system customization cost (0.234), maintenance and repair costs (0.283), operating cost (0.417), integration cost (0.535), staff training cost (0.547), and reduction in manpower requirements (0.7). These indicators are ranked in descending order of importance, from first to eighth respectively

Table 6
Results related to cost sub-criteria

Cost criterion				
Sub-criterion	S	R	Q	Rank
Installation and Commissioning	0	0	0	1
Maintenance and Repairs	0.363	0.171	0.283	4
System customization	0.307	0.133	0.234	3
Reducing the need for manpower	0.917	0.4	0.7	8
Staff training	0.729	0.3	0.547	7
Operational cost	0.479	0.311	0.417	5
Infrastructure	0.208	0.085	0.156	2
Integrity	0.738	0.266	0.535	6

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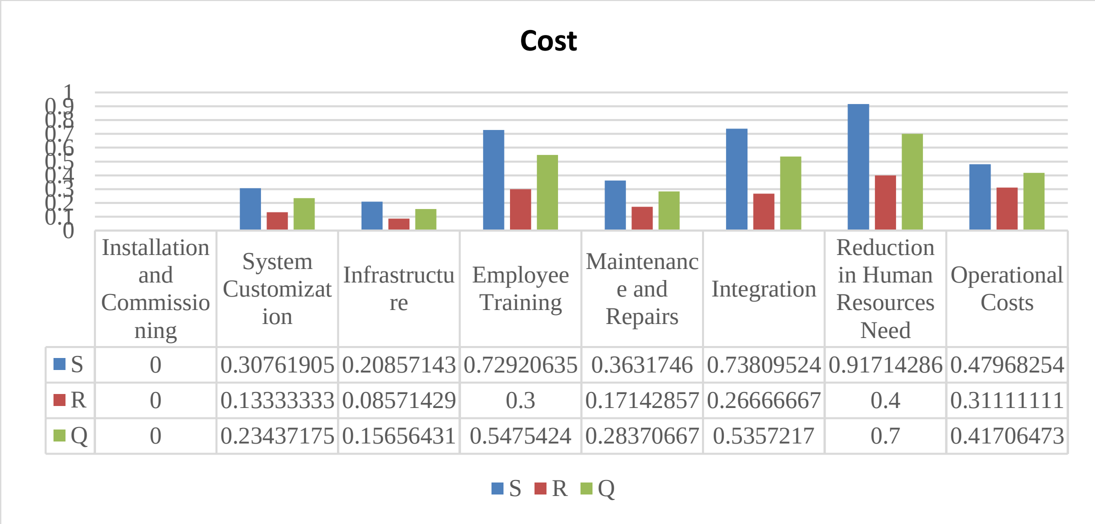

Figure 2. The results related to the cost sub-criterion analysis (a lower Q level indicates a more favorable situation)

Table 7 and Figure 3 present the results pertaining to the analysis of the agility sub-criterion. As observed in the table, the findings in this section reveal that the Vikor index is as follows: flexibility (0), speed (0.092), sensitivity and responsiveness (0.117), and competence (0.246), which are ranked from first to fourth, respectively, in terms of importance level.

Table 7
Results related to agility sub-criterion

Agility criterion				
Sub-criterion	S	R	Q	Rank
Sensitivity and responsiveness	0.23	0.18	0.117	3
Flexibility	0.2	0	0	1
Speed	0.246	0.1	0.092	2
Competence	0.75	0.4	0.7	4

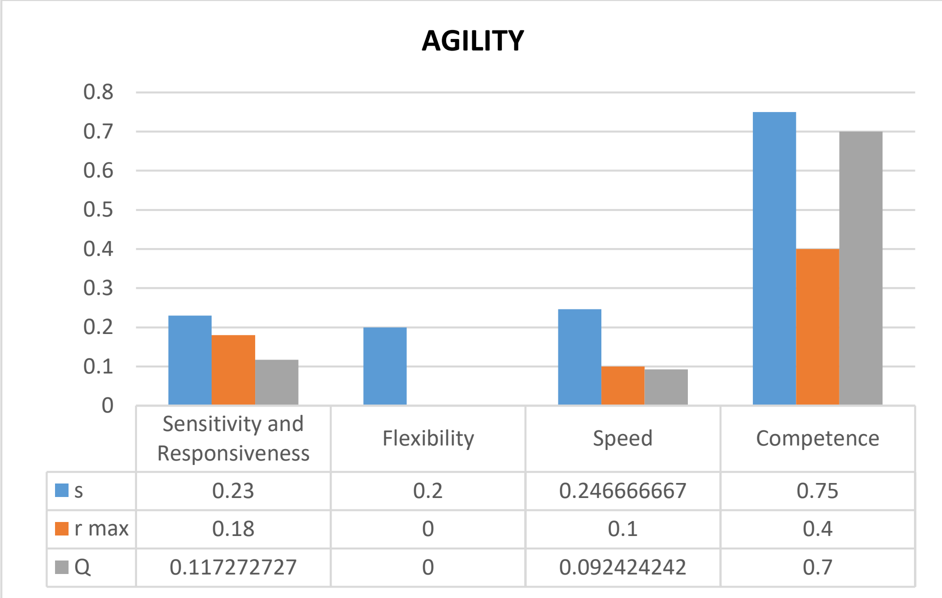

Figure 3. The results related to the analysis of the sub-criterion of agility (a lower Q level indicates a more favorable situation)

Table 8 and Figure 4 illustrate the outcomes concerning the analysis of security sub-criteria. As depicted in the table, the findings in this section indicate that the Vikor index values are as follows: availability of system components (-0.225), confidentiality (0.0314), vulnerability to attacks (0.232), encryption technique (0.265), reliability (0.3125), and data integrity (0.359). These are ranked from first to sixth, respectively, in terms of importance level.

Table 8
Results related to security sub criteria

Criteria: Security				
Sub criteria	S	R	Q	Rank
Reliability	0.412	0.26	0.211	5
Confidentiality	0.023	0.014	0.123	2
Encryption Techniques	0.112	0.026	0.157	3
Susceptibility to Attacks	0	0	0	1
System Component Availability	0.228	0.16	0.318	6
Data Integration	0.213	0.124	0.182	4

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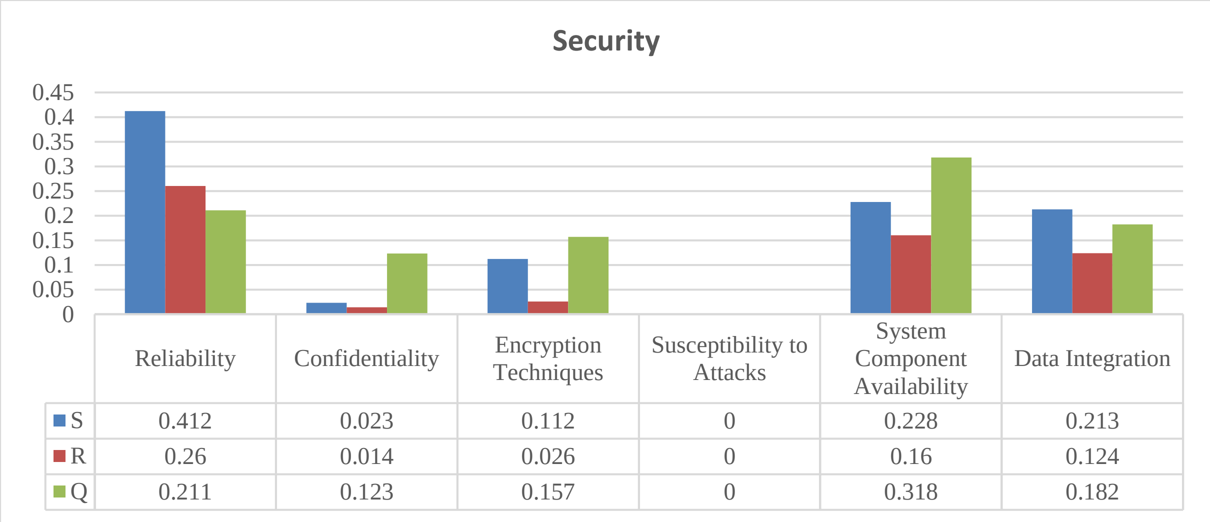


Figure 4. The results related to the analysis of security sub-criteria (a lower Q value indicates a more favorable situation)

Table 9 and Figure 5 display the findings concerning the analysis of the technology criteria that follow. As seen in the table, the results in this section indicate that the Vikor index values are as follows: Internet of Things (0), machine-to-machine wireless network communication (0.124), radio identification technology (0.287), robots (0.297), simulation (0.330), sensors (0.369), 3D printer (0.489), decision support system (0.491), cloud computing (0.630), big data (0.647), and data mining (0.7). These are ranked from first to eleventh, respectively, in terms of importance level.

Table 9
Results related to technology sub-criteria

Criteria: Technology									
Sub criteria	S	R	Q	Rank	Sub criteria	S	R	Q	Rank
Radio Frequency Technology	0.336	0.15	0.287	3	3D Printing	0.546	0.290	0.489	7
Data Mining	0.794	0.4	0.7	11	Internet of Things	0	0	0	1
Simulation	0.351	0.218	0.330	5	Machine-to-Machine Communications	0.139	0.072	0.124	2
Big Data	0.790	0.3	0.647	10	Sensors	0.428	0.2	0.369	6
Robots	0.356	0.145	0.297	4	Decision Support System	0.549	0.290	0.491	8
Cloud Computing	0.741	0.327	0.630	9	-	-	-	-	-

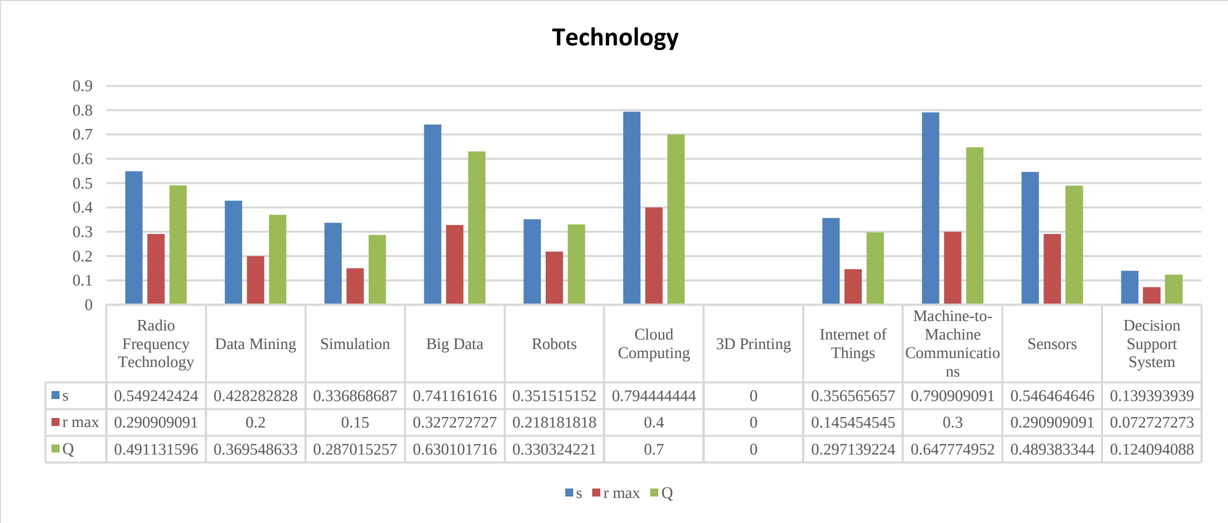
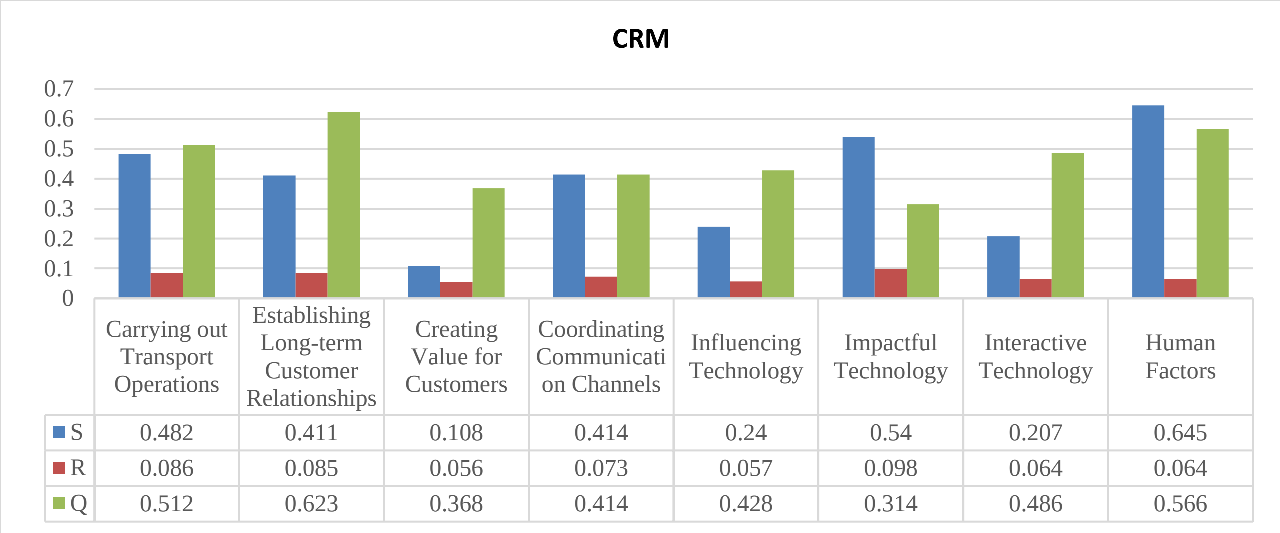


Figure 5. The results related to the analysis of technology sub-criteria (a lower Q level indicates a more favorable situation)

Table 10 and Figure 6 provide the results regarding the analysis of customer relationship management sub-criteria. As observed in the table, the findings in this section reveal that the Vikor index values are as follows: having a long-term relationship with the customer (0.314), interactive technology (0.368), human factors (0.414), conducting transportation operations (0.428), creating added value for customers (0.486), employing effective technology (0.512), coordinating communication channels (0.566), and utilizing efficient technology (0.623). These are ranked from first to eighth, respectively, in terms of importance level.

Table 10
The results related to customer relationship sub-criteria

Criteria: Customer relationship management									
Sub criteria	S	R	Q	Rank	Sub criteria	S	R	Q	Rank
Carrying out Transport Operations	0.240	0.057	0.428	4	Influencing Technology	0.482	0.086	0.512	6
Establishing Long-term Customer Relationships	0.549	0.098	0.314	1	Impactful Technology	0.411	0.085	0.623	8
Creating Value for Customers	0.207	0.064	0.486	5	Interactive Technology	0.108	0.056	0.368	2
Coordinating Communication Channels	0.645	0.064	0.566	7	Human Factors	0.220	0.073	0.414	3



	Carrying out Transport Operations	Establishing Long-term Customer Relationships	Creating Value for Customers	Coordinating Communication Channels	Influencing Technology	Impactful Technology	Interactive Technology	Human Factors
S	0.482	0.411	0.108	0.414	0.24	0.54	0.207	0.645
R	0.086	0.085	0.056	0.073	0.057	0.098	0.064	0.064
Q	0.512	0.623	0.368	0.414	0.428	0.314	0.486	0.566

Figure 6. Results related to the analysis of customer relationship management sub-criteria (a lower Q level indicates a more favorable situation)

As can be seen, in the final comparison of the supply chain intelligence criteria in terms of their importance, the criteria of cost, technology, security, customer relationship management, and agility with the weight of the best-worst group fuzzy technique are respectively equal to (0.301), 0.216), (0.188), (0.171) and (0.121) have obtained the first to fifth ranks. In Figure 7, the developed model resulting from the research is presented.

5. Managerial insights

- Given the importance of profitability and cost reduction, and considering that the expenses related to installation, commissioning, and infrastructure preparation are deemed the most significant costs by experts, it is essential to provide suitable economic justification plans to automakers. This will lead them to appreciate the importance of competition and the adoption of intelligent supply chain practices.
- Flexibility and speed are factors directly tied to an organization's survival in a competitive environment. If the supply chain isn't intelligent, the organization's flexibility, speed, and proactive response to evolving needs will be hindered. Therefore, it is crucial to recognize the importance of initial infrastructure investment costs, and consider them with a long-term perspective, just as is done in other fields.
- Any technology used must be fully secure, reliable, and integrated in terms of security. If the technology in use is subjected to attacks, experiences fluctuations in service provision, or fails to uphold the confidentiality of customers and suppliers (i.e., the entire supply chain), it leads to dissatisfaction and inefficiency. Therefore, the adoption of technologies like the Internet of Things necessitates the establishment of trust capabilities across the entire supply chain. Among technologies such as robots, sensors, and tag readers, in addition to cost considerations, security is always a crucial concern. Hence, automakers must select the implemented technology with careful consideration and expertise.
- Demand Forecasting: Utilizing predictive models and analyzing data related to the demand for parts and vehicles can assist automakers in more accurately determining what needs will arise in the future. This, in turn, enables them to optimize production and distribution planning.

- Employee Training and Skill Development: With technological advancements and evolving work methods, it is imperative to enhance the skills of employees in the field of smartification. Appropriate training for teams helps them gain greater proficiency in utilizing new technologies, thereby boosting productivity.
- Environmental Impact Analysis: The development of supply chain smartification is directly associated with environmental impacts. It is essential to analyze and assess these impacts, including economic, social, and environmental effects, and formulate corresponding plans accordingly.
- Promoting a Culture of Smartification: Fostering a culture of smartification within the organization and throughout the entire supply chain, including suppliers and customers, should be established as a significant management goal. This culture can lead to enhanced collaboration and knowledge sharing across the entire supply chain.

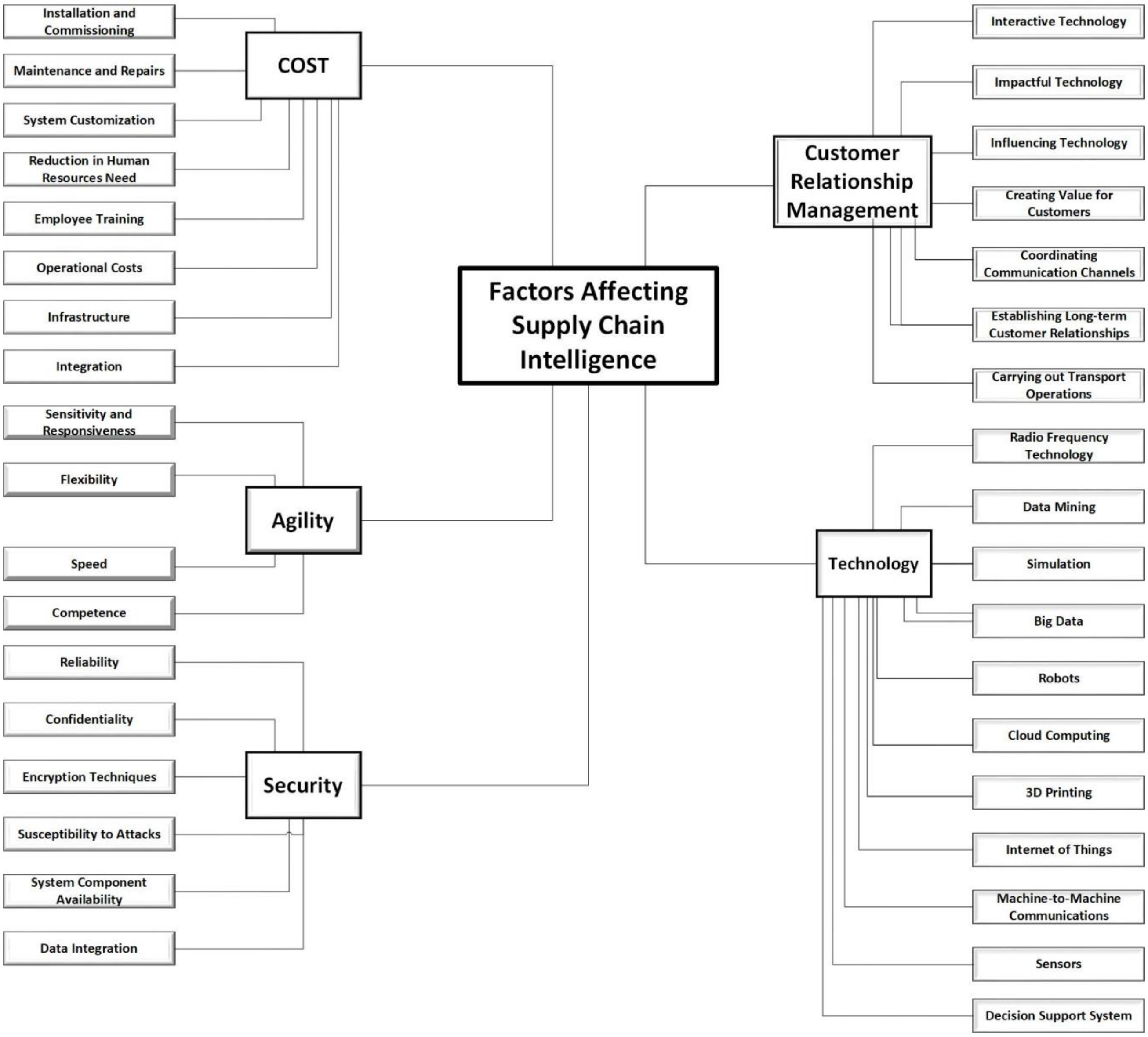


Figure 7. Proposed model for evaluating the factors affecting supply chain intelligence based on research findings

6. Conclusion

Supply chain smartness is a crucial factor for improving the performance and competitiveness of various industries. However, there is a lack of a systematic framework that can identify and evaluate the key criteria for achieving supply chain smartness [31-33]. For this purpose, the current research has been carried out in line with the development of a model to evaluate the criteria that play a role in improving supply chain smartness, and in the research method, after identifying the criteria, using the combined multi-criteria decision-making technique based on Vikor and the best-worst ratio of prioritizing the criteria and Evaluating them is a countermeasure. The results demonstrate that supply chain intelligence significantly contributes to improving productivity. While various factors influence the effectiveness of supply chain intelligence, the cost dimension emerges as particularly pivotal. Since the supply chain aims to minimize the total costs of ordering and keeping goods, the research experts thought that they would witness such an event with chain intelligence and one of the reasons that managers tend towards intelligence is because of the cost reduction that managers can achieve with chain intelligence. Provide a significant portion of fixed costs and reduce transportation costs. Also, safety stock is kept because when the demand is higher than the expected amount or the goods are received later than the due date, we will see a change in this procedure with the smartening of the chain.

Reducing costs, increasing the speed of product preparation and delivery, improving security, using the right tools for smartening, and improving communication with customers can all be among the results of implementing a successful model of smartening the supply chain and, as a result, successful business. In this study, the influencing criteria for improving supply chain smartness have been investigated. For this purpose, a new hybrid approach based on the best-worst group fuzzy method has been used. The results of the current research show that according to the reviewed criteria, which criteria are more important for smartening the supply chain and need special attention, also important sub-criteria have been identified and ranked.

In this study, the focus of the evaluation was on the supply chain of the factory. In future research, all parts of the factory such as warehouse and procurement, queue and headquarters departments, etc. can be evaluated for intelligence. In today's competitive and innovative environment, where other influential factors are involved in the investigation of supply chain intelligence, it is suggested to investigate other influential factors by using other influential models.

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Conflicts of Interest
The authors declare no conflicts of interest.

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