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HYBRID MACHINE LEARNING-BASED MODEL FOR EVALUATING THE PERFORMANCE OF AGILE-SUSTAINABLE SUPPLY CHAINS IN THE CONTEXT OF INDUSTRY 4.0: A CASE STUDY

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Abstract. In today's world, businesses and, in general, supply chains have undergone extensive transformations, and relying solely on traditional metrics such as cost and quality cannot provide a comprehensive and complete evaluation of companies active in various sections of supply chains. One of the main concerns of supply chain managers is to create an integrated and comprehensive structure for evaluating the performance of active branches. In this context, this study presents a structure that, by simultaneously considering agility and sustainability metrics within the context of the industry 4.0, which has brought about fundamental changes in the supply chain environment in recent years, aims to evaluate the active branches in the dairy product supply chain. On the other hand, the increase in the volume of data produced in the supply chain environment and the development of the applications of machine learning algorithms in various fields, which offer better applications compared to intuitive approaches, have led this study to use hybrid data-driven approaches, which are a combination of expert-based methods and documented organizational data, to evaluate the performance of supply chain branches. Therefore, this study is innovative in terms of the evaluation metrics and the data-driven approach developed. In the first step, evaluation metrics appropriate to the dimensions of agility, sustainability, Industry 4.0, and general metrics were identified, and then the fuzzy best-worth method (FBWM) approach was used to weight the metrics. According to the findings, data-driven, marketing, overhead costs, delivery timeframe, and product quality were selected as the most important metrics. Subsequently, using the developed artificial neural network algorithm, which calculates the input weights of the metrics using the FBWM method, a model for evaluating the supply chain was presented, and the findings show that the developed approach performs better than other algorithms on the problem data with more than 92% accuracy.

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1. Introduction

In recent decades, the supply chain has become a crucial element in the success of organizations. This importance stems from the supply chain's fundamental role in optimizing processes, reducing costs, and enhancing customer satisfaction on a global scale [21]. In today's world, marked by significant technological advancements and increased demand for customized products and services, the importance of supply chain management has intensified [31]. These environmental and market changes compel organizations to rethink their supply chain strategies and adopt innovative methods to maintain competitiveness [6].

Evaluating the performance of subsidiaries of a central organization plays a key role in identifying strengths, weaknesses, opportunities, and threats [37]. This process allows managers to focus more accurately on continuous improvement and enhancing efficiency and effectiveness. In this regard, performance evaluation acts as a strategic tool that facilitates data-driven decision-making and enables organizations to quickly respond to market changes [17,31]. Therefore, it is important for organizations to be able to evaluate performance based on various effective indicators and components.

With the advent of the industry 4.0, the use of advanced technologies such as machine learning, artificial intelligence, the Internet of Things (IoT), and big data has created new capacities for improving the supply chain [32]. Thus, it is important that subsidiaries within a central supply chain can evaluate their performance considering the indicators of the industry 4.0, moving the organization towards the industry 4.0. Establishing digitization infrastructure in supply chains, which significantly impacts other dimensions such as agility and resilience, is important in today's era [10, 26].

On the other hand, the component of agility has become increasingly critical in today's world due to the accelerated pace of operations and heightened customer expectations [19]. Agility within the supply chain and its branches refers to the capacity to swiftly respond to market fluctuations, customer demands, and unpredictable environmental conditions [26]. This concept is essential for organizations striving to maintain competitiveness and flexibility in the face of rapid innovations and unforeseen changes [7]. Agility empowers supply chains and their branches to meet customer requirements by shortening product delivery times and enhancing service quality [19]. Furthermore, it enables organizations to manage resources more efficiently, minimize waste through improved coordination and collaboration across the supply chain, and reduce costs [27].

Another crucial component in the context of supply chains is sustainability. Sustainability in the supply chain involves the integration of environmental, social, and economic goals into the processes and decision-making activities related to the supply chain [2]. This approach not only helps mitigate negative environmental impacts but also enhances relationships with stakeholders, increases customer trust, and fosters a socially responsible brand [29]. In today's world, consumers and organizations are increasingly seeking business partners who acknowledge and implement sustainability values in their operations [2, 11]. Sustainability aids organizations in managing environmental and social risks while simultaneously improving operational efficiency and securing long-term competitive advantages [26]. Therefore, incorporating sustainability components in performance evaluation is of paramount importance.

Given the explained points, it can be observed that evaluating the performance of organizational branches in the supply chain is crucial, especially in the dairy industry due to the various sensitivities of the products. The main motivation of this study is to develop a model that continuously evaluates the performance of organizational branches in the dairy supply chain and monitors their activities based on various metrics at any given moment. In the dairy industry, sustainability is important due to environmental and social concerns, agility is significant because of the short consumption period of the products, and attention to digitization components is essential due to the importance of Industry 4.0 technologies in today's businesses. Therefore, the primary goal of this study is to develop a performance evaluation model that provides a comprehensive assessment by considering not only general metrics but also sustainability, agility, and Industry 4.0 indicators. Additionally, most studies in this field have been conducted based on intuitive approaches, relying on expert opinions to evaluate the performance of organizational units, which can lead to human errors. This study employs hybrid data-driven methods that offer high speed and flexibility, allowing for much more accurate performance evaluations of organizational units compared to intuitive approaches. Therefore, the main innovations of this study are the simultaneous consideration of agility, sustainability, and Industry 4.0 metrics alongside general metrics in evaluating the performance of dairy supply chain units, and the use of hybrid data-driven approaches.

The remainder of this study is structured as follows; Section 2 reviews the literature, Section 3 presents the case study and solution methodology, Section 4 discusses the findings, and Section 5 provides conclusions and future recommendations.

2. Literature review

2.1. Related works

In this section, studies that focus on the evaluation of supply chain performance in various segments such as suppliers, distributors, or the entire supply chain cycle in alignment with the paradigms of agility, sustainability, and Supply Chain 4.0 are briefly reviewed. For instance Sangari *et al.* [28] developed a framework for assessing performance, aimed at pinpointing essential agility factors within supply chains. Their research commenced with the identification of agility metrics suitable for the evaluation of supply chains across various organizations, achieved by consulting expert opinions. Subsequently, they applied a hybrid methodology incorporating DEMATEL (Decision Making Trial and Evaluation Laboratory) and ANP (Analytic Network Process) to assign weights and assess these indicators, specifically tailored to the automotive sector. The findings of their study highlighted the critical importance of parts supply flexibility, rapid response capability, and swift delivery times as key agility metrics for organizations. Valilai and Sodachi [34] employed indicators of the industry 4.0 to create a model for assessing sustainability within supply chains. Their research involved identifying relevant indicators for supply chain evaluation, followed by the development of a model based on Markov decision processes (MDP) to assess organizational performance. Rahimi *et al.* [22] carried out research focused on identifying a suitable site for the disposal of urban solid waste, emphasizing sustainability. The evaluation framework for potential sites was structured around three pillars of sustainability: economic, environmental, and social factors. The weighting of these criteria was performed through the best-worst method. The study highlighted that the proximity to water bodies, roads, and urban centers emerged as the most significant criteria. Following this, the site selection process involved weighting and ranking the alternatives by integrating the MULTIMOORA method with Geographic Information Systems (GIS).

Sazvar *et al.* [29] developed a data-driven approach to assess and choose suppliers, focusing on sustainability and resilience. Their study pinpointed 22 key factors, applying the Fuzzy Best-Worst Method (FBWM) to calculate the importance of these factors and the Fuzzy Inference System (FIS) to devise criteria for evaluating supplier performance. Machine learning techniques were also utilized to create a model for supplier evaluation. The research highlighted that manager give precedence to responsiveness and capability. This model can be adopted by other companies for their supplier selection endeavors, taking advantage of past data for decision-making. On a related note, Shao *et al.* [30] explored the selection of sustainable and resilient suppliers amidst the disruptions brought about by the COVID-19 pandemic. They introduced a multi-objective mathematical model, solved *via* the novel nRa-NSGA-II algorithm, focusing specifically on the supply chain for medical equipment during the pandemic, with a keen emphasis on resilience. Fathi *et al.* [3] conducted an analysis on the sustainability of supply chains within the transportation sector. They applied an advanced version of the data envelopment analysis technique to assess the efficiency of these supply chains. The primary input metrics considered in their analysis included the workforce size, road network extent, availability of public transport, and fuel usage. Conversely, the outcomes were evaluated based on criteria such as passenger volume, incidence of road accidents, carbon dioxide emissions, and the rate of passenger fatalities. Xin *et al.* [35] assessed the difficulties associated with executing a sustainable supply chain 4.0 within the context of a circular economy. Their research utilized an enhanced multi-criteria decision-making strategy, founded on the SWARA method, alongside advanced measurement techniques. Key challenges pinpointed in their study encompass inadequate coordination and integration, insufficient infrastructure and internet connectivity, along with poor data quality.

Razeghi *et al.* [24] introduced an approach based on multi-criteria decision-making for the selection of solar energy sites within Iran. The evaluation of prospective sites was conducted based on critical factors including the initial installation costs, proximity to urban areas, and environmental considerations. The Analytic Hierarchy Process (AHP) was utilized to assign weights to these criteria, followed by the application of the VIKOR method for site assessment. According to their analysis, Khansar emerged as the optimal location for the development of a solar energy site. Tavakoli *et al.* [33] introduced a novel decision-making framework combining Markov processes and fuzzy logic for evaluating suppliers in a way that is both resilient and customer-based. Their research targeted the supplier selection process for online marketplaces. Initially, the study applied a fuzzy best-worst method to assign preliminary weights to various criteria, which were then refined through Markov chain analysis to determine their final significance. Subsequently, the Quality Function Deployment (QFD) method was employed to assess and rank the suppliers. The outcomes highlighted the primary importance of cost, availability, and performance at the outset. However, from a customer perspective, the emphasis shifts towards quality, on-time delivery, and heightened responsiveness. ForouzeshNejad [4] focused on the issue of selecting suppliers for a medical equipment company during the COVID-19 pandemic, incorporating principles from Lean and Agile methodologies, Sustainability, and Industry 4.0 concepts. He used the rough best-worst method (RBWM) to allocate weights to various identified criteria. Following this, he evaluated and ranked potential suppliers by analyzing their data against these criteria through the use of the interval rough multi-attributive border approximation area comparison (IR-MABAC) technique.

Rostami *et al.* [26] conducted an assessment of medical equipment suppliers through the lens of sustainable supply chain principles. Their research introduced an innovative methodology that merges multi-criteria decision-making with optimal planning techniques. The results revealed that attributes such as lean-agility, stability, and resilience, each bearing similar significance, are deemed crucial within this sector, whereas factors related to digitalization were found to be of lesser importance. Utilizing the novel approach for weighting indicators, and employing the TOPSIS and VIKOR methods, the researchers calculated the relative importance of each supplier, subsequently comparing these outcomes. Krstić *et al.* [14] have evaluated the risks associated with the agri-food supply chain, taking into account the circular economy. They assessed seven main risk groups in relation to nine criteria. To address this issue, a novel MCDM model was developed that integrates the best-worst method (BWM) and the comprehensive distance-based ranking (COBRA) method within a grey environment. Their findings specifically indicate that risks related to product features, logistics risks, and managerial risks are of paramount importance. The summary and classification of the literature review is shown in Table 1.

2.2. Research gaps and contributions

The topic of performance evaluation at various levels of the supply chain has been of interest to researchers for several decades. Given the various changes in business conditions, this subject remains relevant and never becomes outdated. As shown in Table 1 and the reviewed literature, studies in the field of supply chain evaluation often focus on specific parts of the supply chain. For example, Sazvar *et al.* [29], Shao *et al.* [30], Tavakoli *et al.* [33], ForouzeshNejad [4] have evaluated the performance of suppliers, or Rahimi *et al.* [22] have evaluated the performance of distributors. Few studies have comprehensively addressed this issue in the dairy industry. Therefore, considering all dimensions of the supply chain in performance evaluation, this study aims to fill the research gap in the dairy industry studies. Additionally, no study was found that simultaneously considers sustainability, agility and Industry 4.0 indicators in the evaluation of the dairy supply chain. This study also addresses this research gap. Moreover, the use of hybrid data-driven models in supply chain performance evaluation has not been observed in other studies, thus filling another research gap. In summary, the innovations of this study in addressing research gaps include (I) the lack of studies that comprehensively consider all sections of the supply chain, including suppliers, manufacturer, and distributors in the dairy industry, (II) the absence of studies that simultaneously consider sustainability, agility, and Industry 4.0 indicators alongside general indicators, and (III) the lack of studies that use hybrid data-driven models for evaluating the performance of the dairy supply chain.

Table 1. Classifying the related studies.

Study	Supply chain part			Criteria			Data-driven	Methodology	Case study
	Supplier	Manufacturer	Distributor	Agility	Sustainability	Industry 4.0			
Sangari *et al.* [28]	*	*	*	*				DEMATEL – ANP	Automobile
Valilai and Sodachi [34]		*	*			*		Markov Chain	–
Rahimi *et al.* [22]			*		*			BWM - MULTIMOORA	Solid waste landfill
Sazvar *et al.* [29]	*				*		*	FBWM – FIS – SVM	Pharmaceutical
Shao *et al.* [30]	*			*	*			ANP-DEMATEL- Extended MOORA-SAW	Automobile industry
Fathi *et al.* [3]	*	*	*		*			Novel robust two-stage network DEA model	Transportation
Xin *et al.* [35]	*	*	*		*	*		q-ROF-SWARA-COPRAS	Manufacturer
Razeghi *et al.* [24]		*	*		*			AHP - VIKOR	Solar energy site
Tavakoli *et al.* [33]	*				*			BWM-Markov-QFD	Online marketplace
ForouzeshNejad [4]	*			*		*		IR-MABAC	Medical equipment
Rostami *et al.* [26]	*			*	*	*		Goal programming-based FBWM	Medical device
Krstić *et al.* [14]	*	*	*		*			Hybrid BWM-COBRA	Agri-food
This study	*	*	*	*	*	*	*	FBWM – WANN	Dairy products

3. Case study and methodology

3.1. Case study and indicators

The case study of this article focuses on a dairy product manufacturing and distribution company in Iran. This company handles all stages of raw material procurement, product manufacturing, and distribution to retailers comprehensively. The company has divided Iran into 10 branches, with each branch independently managing all activities and processes from raw material procurement to distribution. One of the main issues and challenges for senior management is the performance evaluation of these branches. Comprehensive and complete metrics need to be defined to evaluate their performance accurately and thoroughly. On the other hand, performance evaluation in the studied company has been based on individual assessments, which can lead to errors for various reasons. Consequently, the decision was made to develop a data-driven model that, by inputting relevant metric data, can evaluate the performance of the branches at any moment, thereby increasing the speed and flexibility of supply chain branch evaluations. Therefore, the overall structure of the branches and the central organization is shown in Figure 1, where each of the ten branches must plan for procurement, production, and distribution according to the needs of the customers in their respective regions. There are five main suppliers of raw materials for dairy products, providing materials to various branches where the products are manufactured, packaged, and distributed. It is worth mentioning that the data used to develop the data-driven model for evaluating the branches of the dairy supply chain were collected based on real data from the organization studied in Iran.

Therefore, to evaluate each branch, a comprehensive framework based on the components of agility, sustainability, and Industry 4.0, as well as general indicators, must be provided. As previously mentioned, the industry 4.0 metrics refer to digitization metrics, which evaluate companies' performance in utilizing tools and trends in this field. In this regard, Tables 2–5 define the performance evaluation indicators for the branches, separated by each paradigm.

3.2. Fuzzy Best-Worth Method (FBWM)

A relatively new technique that has garnered interest from researchers is the Fuzzy Best-Worst Method (FBWM). The primary benefits of the BWM compared to similar methodologies (*e.g.*, AHP), as highlighted by Rezaei *et al.* [25] and Aria *et al.* [1], include: (i) a significant reduction in computational demands, (ii) enhanced

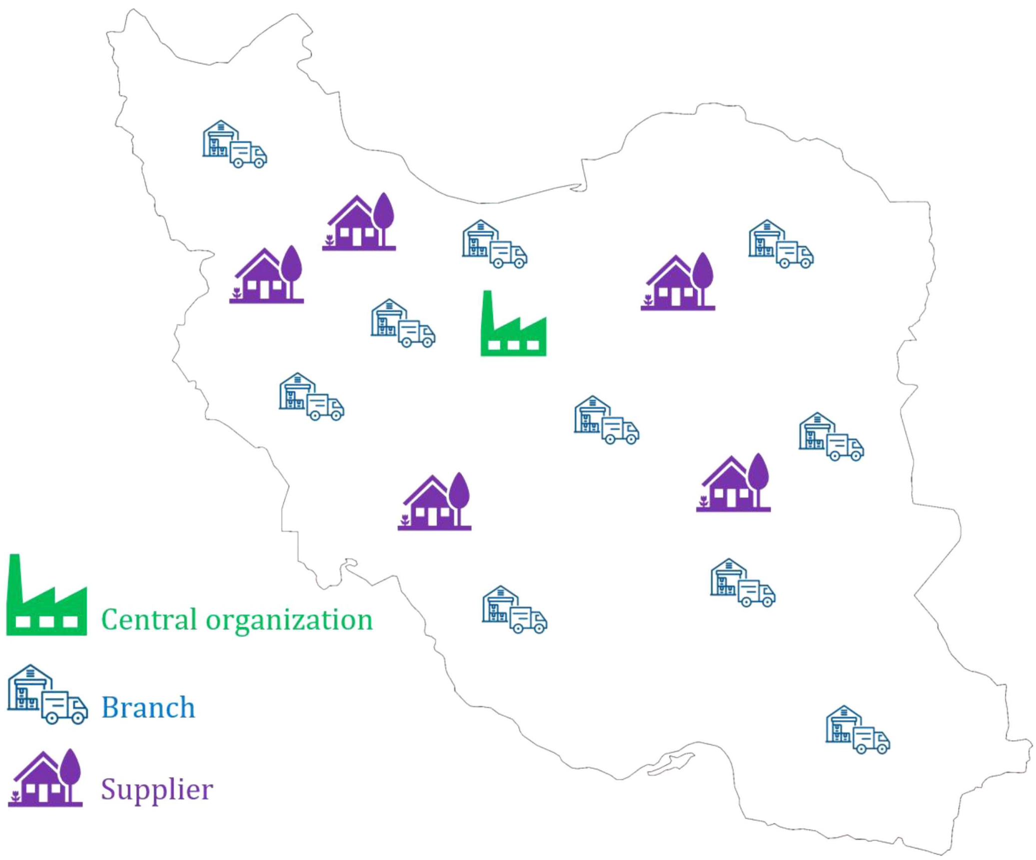

Figure 1. Research case study structure.

Table 2. Agility indicators.

Indicator	Description	References
Delivery Timeframe	This metric represents the interval between placing an order and the product's delivery to the customer	Rostami *et al.* [26]
Product Quality	This reflects the rate of customer satisfaction regarding the quality of products	ForouzeshNejad [4]
Process velocity	Measures the rapidity of workflow among different departments within the supply chain	Rostami *et al.* [26] Sazvar *et al.* [29]
Responsiveness	The percentage of the number of orders that are answered by the supply chain	ForouzeshNejad [4]
Communication level	The score of ease of communication in the supply, production and distribution departments with the branch	ForouzeshNejad [4]

Table 3. Sustainability indicators.

Indicator	Description	References
Retention rate of human resources	The average duration of human resources activity in the branch	Rostami *et al.* [26]
Stakeholder satisfaction	The weighted average of the branch's performance score for various stakeholders, including employees, shareholders, senior managers, etc.	Tavakoli *et al.* [33]
Fuel consumption	Average fuel consumption in different logistics, production and etc.	Sazvar *et al.* [29]
Environmental certificate	The number of certificates related to environmental standards in the branch	Kusi-Sarpong *et al.* [15]
Financial efficiency	It expresses the profitability of the company	Khan *et al.* [13]

Table 4. Industry 4.0 (Digitalization) indicators.

Indicator	Description	References
Smartification	Percentage of branch activities that are done intelligently	Rostami *et al.* [26]
Data-driven	The amount of use of available data and data-driven analyzes in the planning of different sectors, including demand, production, supply, etc.	Kusi-Sarpong *et al.* [15]
Security level	The score related to the level of data security and the organization's activities	Hosseini Dolatabad *et al.* [9], Rostami *et al.* [26]
Virtual activity	The amount of presence in website platforms, social networks and applications and support	Kusi-Sarpong *et al.* [15]

Table 5. General indicators.

Indicator	Description	References
Overhead costs	The ratio of overhead costs to the volume of production and branch performance	Rasmussen *et al.* [23]
Flexibility	Capability and degree of flexibility against changes in demand, requests of the central organization and related matters	Hosseini Dolatabad *et al.* [9]
Robustness	It expresses resilience against sudden crises and challenges	Khan *et al.* [13]
Marketing	The ratio of the market share of the branch in the target area compared to the past time periods	Tavakoli *et al.* [33]

TABLE 6. Conversion chart for linguistic terms [36].

Linguistic terms	Of Equal Significance (ES)	Slightly Significant (SS)	Moderately Significant (MS)	Highly Significant (HS)	Critically Essential (CE)
Membership function	(1, 1, 1)	(0.667, 1, 1.5)	(1.5, 2, 2.5)	(2.5, 3, 3.5)	(3.5, 4, 4.5)

TABLE 7. Consistency Index (CI) derived from You *et al.* [36].

$\tilde{a}_{\mathbf{BW}}$	ES	SS	MS	HS	CE
CI	3.00	3.80	5.29	6.69	8.04

reliability of results, (iii) decreased time required for pairwise comparisons, and (iv) ease of integration with other methods. However, in general, the use of FBWM in this study is due to the ease of understanding and comprehending its questionnaire for experts, as well as the high speed of completing the questionnaire data. Additionally, it accurately assesses the weights of the metrics.

Before delving into the steps of the FBWM, it is important to understand that $\tilde{a} = (l, m, u)$ represents a triangular fuzzy number, and the Graded Mean Integration Representation (GMIR), denoted as $R(\tilde{a})$, is computed in the manner described.

$$R(\tilde{a}) = \frac{l + 4m + u}{6}\cdot \tag{1}$$

The procedure for applying the Fuzzy Best-Worst Method (FBWM), as outlined by Guo and Zhao [5], is as follows:

- Step One involves identifying the most and least favorable indicators, drawing upon expert judgments.
- Step Two entails the construction of Best-to-Other (BO) and Other-to-Worst (OW) vectors, utilizing the linguistic terms detailed in Table 6. Here, 'B' denotes the top-performing indicator, while 'W' represents the lowest. Consequently, the BO vector is expressed as $\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \ldots, \tilde{a}_{Bn})$, and the OW vector is articulated as $\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \ldots, \tilde{a}_{nW})$.
- Step Three; calculating optimal weights through the mathematical model. For this purpose, let's assume $\tilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$, $\tilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$, $\tilde{w}_j = \left(l_j^w, m_j^w, u_j^w\right)$ and $\tilde{\xi}^* = (k^*, k^*, k^*)$. Below is the mathematical formulation for the FBWM.

$$\min \tilde{\xi}^* \tag{2}$$
$$\text{s.t.} \begin{cases} \left|\frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj})\right| \le (k^*, k^*, k^*) \; \forall \text{j} \\ \left|\frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW})\right| \le (k^*, k^*, k^*) \; \forall \text{j} \\ \sum_{j=1}^{n} R(\tilde{w}_j) = 1 \qquad \forall \text{j} \\ l_j^w \le m_j^w \le u_j^w \qquad \forall \text{j} \\ l_j^w \ge 0 \qquad \forall \text{j} \end{cases}.$$

- Step Four involves determining the Consistency Ratio (CR). To do this, the Consistency Index (CI) is first calculated by comparing the highest and lowest ranked indicators (refer to Tab. 7). The CR is then derived using equation (3). It's important to highlight that a CR value closer to zero is preferable, indicating better consistency.

$$CR = \frac{\xi^*}{\mathrm{CI}}. \tag{3}$$

3.3. Weighted Artificial Neural Networks (WANN)

In this section, the artificial neural network method, which calculates the weight of features from another method, is explained. Generally, there are 5 main steps in this algorithm, each consisting of several stages. The artificial neural network algorithm is suitable for this study due to its fast-learning capability, approximation of complex functions, flexibility in data processing, scalability, and the ability to work with unstructured data [8,16]. The steps of this algorithm are briefly described as follows [12,20].

Step 1: Data Preprocessing
- Scaling features: initially, scale the input features so that they all fall within a similar range. This helps the network to learn more easily.
- Integrating weights: weights obtained from another method are combined with the weights from the artificial neural network model in the first run. The importance coefficient of the two approaches is such that the importance of the weights from the FBWM method is 0.75, and the importance of the weights from the neural network model is 0.25.

Step 2: Model Design
- Defining network architecture: the network architecture is determined by the number of layers, the number of neurons in each layer, and the activation functions. In this study, the optimal architecture is selected through trial and error on various architectures.
- Initial weighting: the integrated weights from Step 1 are applied as the initial input weights of the neurons in the input layer of the network.

Step 3: Model Training
- Parameter tuning: training parameters such as learning rate, number of epochs, and batch size are set. The approach to tuning parameters is done by testing the model and trial and error.
- Training: in this stage, the model is trained using training data, which constitutes 80% of the data.

Step 4: Model Evaluation
- Testing: the model is tested using different accuracy indicators and the confusion matrix.
- Retuning: based on the test outputs of the model, parameters are readjusted.

Step 5: Optimization and Iteration
- Iterating the process: based on feedback from previous stages, the training and evaluation process is repeated to achieve the best performance of the model.

3.4. Hybrid methodology

This section details the developed hybrid method presented in this article and its implementation steps in sequence. As stated, this study employs a hybrid approach that combines data-driven methods and expert opinions. Initially, the theoretical foundations and literature were reviewed, followed by surveys from experts to identify supply chain evaluation metrics appropriate for the dimensions of agility, sustainability, and Industry 4.0. For weighting the metrics, expert opinions and the FBWM method were utilized, as the precision of experts in determining the importance of metrics according to organizational strategies surpasses that of documented data. The experts consisted of three groups: the first group included senior managers of organizations active in the dairy supply chain industry, the second group comprised academic professors and supply chain consultants, and the third group included experienced executive managers and specialists in dairy industry companies. Once the metric weights were determined, a model based on the developed artificial neural network algorithm, named WANN, was developed. This model allows for the accurate evaluation of the performance of supply

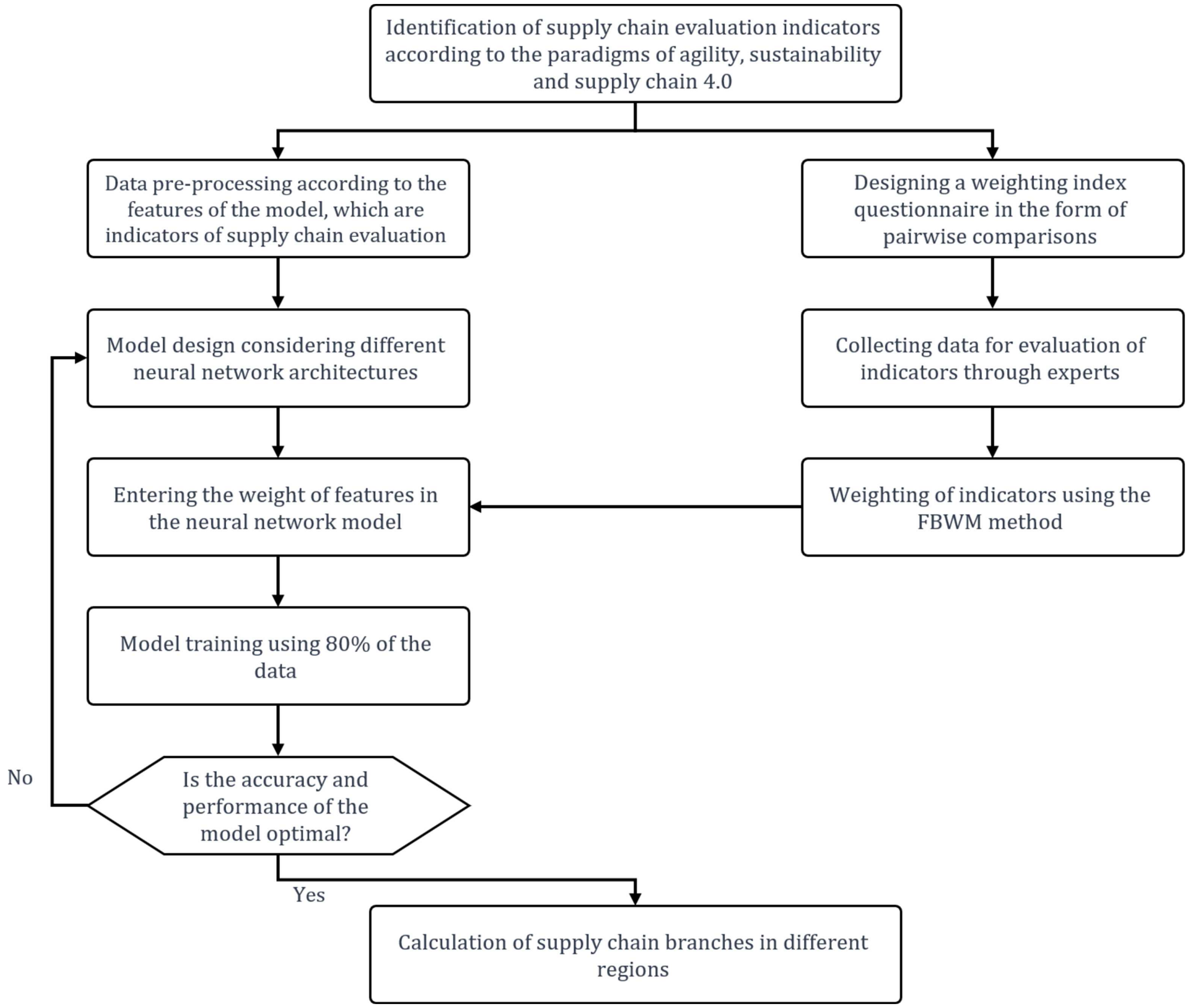

Figure 2. The structure of the developed hybrid method.

chain branches and the assignment of efficiency labels. The developed model is highly flexible, capable of assigning efficiency labels to each supply chain branch individually. After the model's development, its accuracy is measured according to model evaluation metrics.

As shown in Figure 2, the supply chain evaluation indicators are first identified, and in parallel, using expert opinions and the FBWM method, the weights of the indicators are determined, creating the architecture of the artificial neural network. Based on this, the model for evaluating the performance of different branches is developed.

4. Computational results

4.1. The importance of the indicators

In this section, the weights of indicators related to supplier evaluation are calculated. As observed in Figure 3, 18 indicators are categorized into four groups: agility, sustainability, Industry 4.0, and general indicators. The

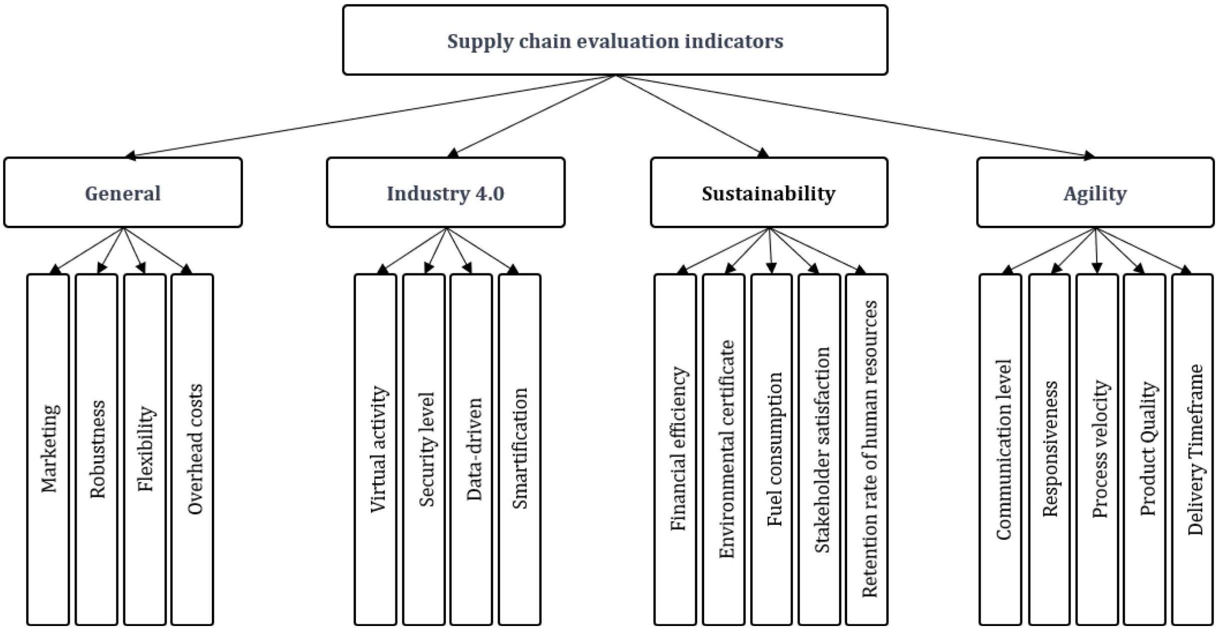

FIGURE 3. Hierarchical structure of indicators.

weighting of the indicators is done hierarchically according to the FBWM method. This means that first, the four categories of indicators are weighted against each other, and then the internal indicators within each category are weighted. In the final step, the final weight of the indicators in comparison to each other is obtained by multiplying the weights of the categories by the weights of the indicators.

In accordance with the established structure and the data collected from a group of experts, the weighting of the indicators has been conducted. The experts were divided into three groups of six individuals each: a group of consultants, academic professors, and researchers in the field of supply chain; a group of senior managers from the organization under study; and a group of operational managers and experienced specialists within the organization. Based on the collected data, the indicators have been weighted, as shown in Table 8. The most important selected indicators include Data-driven, Marketing, Overhead Costs, Delivery Timeframe, and Product Quality. It is noteworthy that profitability indicators consistently emerge as the most critical components for organizations. Additionally, it is highlighted that utilizing data-driven approaches can lead to cost optimization and increased revenue, which is one of the key attractions of Industry 4.0 for leading companies in this sector.

4.2. Performance evaluation of supply chain branches

In this section, a data-driven model based on an artificial neural network for evaluating the performance of supply chain branches is presented. The algorithm utilizes 720 records related to the monthly performance of 10 branches over a six-year period. The features of the model are the same as the supplier evaluation indicators, which include 18 items, and the data are labeled with performance in five states: very poor, poor, average, good, and very good.

For model construction, the weights of the features are applied as inputs, calculated using the fuzzy best-worst method. However, an important note is that in the first step, the correlation coefficient among the indicators is calculated to observe their comparative status and based on this assessment, validate the selection of indicators based on the data. According to Figure 4, the correlation coefficient among the indicators is shown. The interpretation of the correlation coefficient is based on the conditions of Table 9; for example, as seen in Figure 4,

Table 8. Indicators' weights.

Criteria	$W_{Criteria}$	Sub-criteria	$IW_{Sub\text{-}criteria}$	$FW_{criteria}$ = ($W_{Criteria}$ × $IW_{Sub\text{-}criteria}$)
Agility	0.2811	Delivery Timeframe	0.2130	0.0599
		Product Quality	0.2083	0.0586
		Process velocity	0.1991	0.0560
		Responsiveness	0.2037	0.0573
		Communication level	0.1759	0.0494
Sustainability	0.2574	Retention rate of human resources	0.2051	0.0528
		Stakeholder satisfaction	0.2128	0.0548
		Fuel consumption	0.1846	0.0475
		Environmental certificate	0.1897	0.0488
		Financial efficiency	0.2077	0.0535
Industry 4.0 (Digitalization)	0.2249	Smartification	0.2446	0.0550
		Data-driven	0.2844	0.0639
		Security level	0.2324	0.0523
		Virtual activity	0.2385	0.0536
General	0.2367	Overhead costs	0.2560	0.0606
		Flexibility	0.2410	0.0570
		Robustness	0.2349	0.0556
		Marketing	0.2681	0.0635

Table 9. Interpretation of the correlation coefficient.

Correlation	Correlation level
$0 < \lvert r \rvert \leq 0.19$	Very little correlation
$0.2 \leq \lvert r \rvert \leq 0.39$	Low correlation
$0.4 \leq \lvert r \rvert \leq 0.59$	Moderate correlation
$0.6 \leq \lvert r \rvert \leq 0.79$	High correlation
$0.8 \leq \lvert r \rvert \leq 1$	Too much correlation

there is a strong relationship between Delivery Timeframe and Process Velocity, which is well substantiated. Conversely, there is a strong but opposite relationship between Delivery Timeframe and Responsiveness; the lower the delivery speed, typically, the higher the responsiveness percentage. Many indicators also have a weak relationship with each other, due to the different natures of the indicators.

With the relationship among the indicators identified, the desired weighted artificial neural network architecture is developed. To determine the optimal architecture, various parameters including the number of hidden layers, the number of neurons in each layer, activation function, the number of repetitions of the network, network learning rate, type of learning, solver, and momentum must be optimally selected. Through various executions of the developed algorithm, optimal values are estimated. In general, 5 final architectures were selected based on the evaluation of their error rates, from which the optimal architecture was chosen. The selected architectures are shown in Table 10.

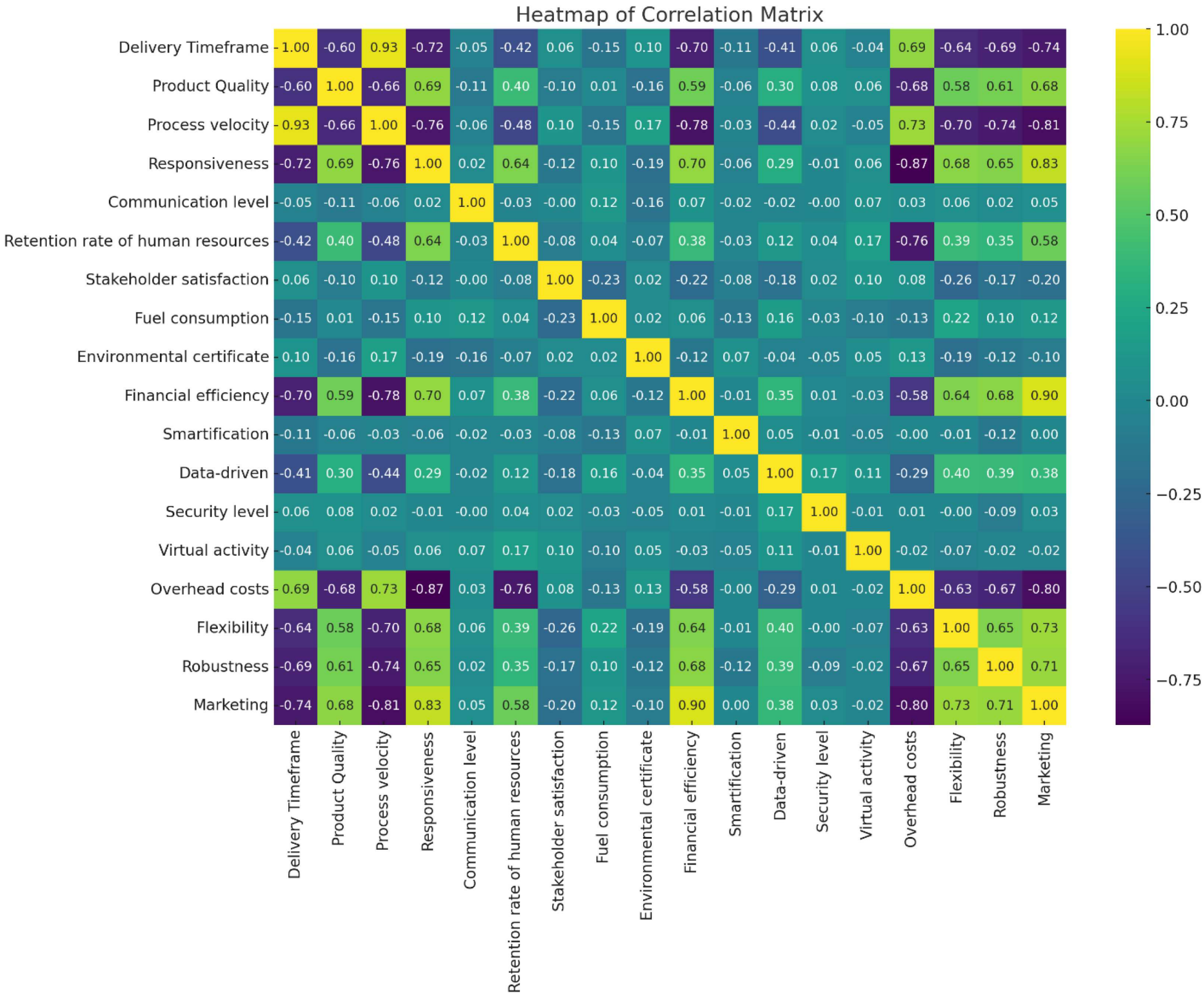

FIGURE 4. Correlation coefficient between indicators.

TABLE 10. Different architectures of developed WANN algorithm.

Hyperparameter	WANN 01	WANN 02	WANN 03	WANN 04	WANN 05
Number of hidden layers	1	1	2	2	2
The number of neurons in each layer	30	60	30	60	90
Activator function	identify	Sigmoid	identify	Tanh	Sigmoid
The number of repetitions of the network	100	100	100	100	100
Network learning rate	0.002	0.004	0.002	0.002	0.004
Network learning type	constant	invscaling	adaptive	constant	invscaling
Solver	adam	adam	sgd	adam	adam
Momentum	0.2	0.4	0.2	0.4	0.6

TABLE 11. RMSE value of different WANN architectures.

Algorithm architecture	RMSE
WANN 01	11.59
WANN 02	10.26
WANN 03	9.65
WANN 04	7.89
WANN 05	8.77

TABLE 12. The performance of different branches of the supply chain.

Branch	Efficiency
Branch 01	Very Good
Branch 02	Average
Branch 03	Good
Branch 04	Poor
Branch 05	Good
Branch 06	Average
Branch 07	Very Good
Branch 08	Very Good
Branch 09	Very Poor
Branch 10	Good

To select the optimal model, the error rates of different architectures are calculated using the Root Mean Square Error (RMSE) and equation (4). The model with the lowest error is chosen as the optimal architecture.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}. \tag{4}$$

Table 11 shows the RMSE values for different WANN architectures. It is observed that the WANN 04 architecture has the least error and is selected as the optimal architecture.

Now, in accordance with the selected architecture, the performance of different branches of the supply chain under study is evaluated. Table 12 displays the performance of the branches, where it is observed that Branches 01, 07, and 08 are selected as the best branches, and Branch 09 is identified as the weakest branch.

4.3. Performance of the FBWM

To evaluate the performance of the methods used in this study, a comparison is presented between the methods utilized and other methods. In Figure 5, it is observed that the Consistency Ratio (CR) in the FBWM method, as compared to BWM, FAHP, and AHP methods, is evaluated. A lower CR indicates a better evaluation and higher accuracy. According to the findings shown in Figure 5, the CR value for the FBWM method is lower than that of other methods such as AHP, FAHP, and BWM across all evaluation dimensions. This demonstrates the superior efficiency and performance of the FBWM method in this study compared to the other methods.

4.4. Performance of the WANN

In this section, the performance of the developed WANN algorithm is examined. For this purpose, the confusion matrix is initially used. In classification algorithms, the confusion matrix is utilized to estimate the

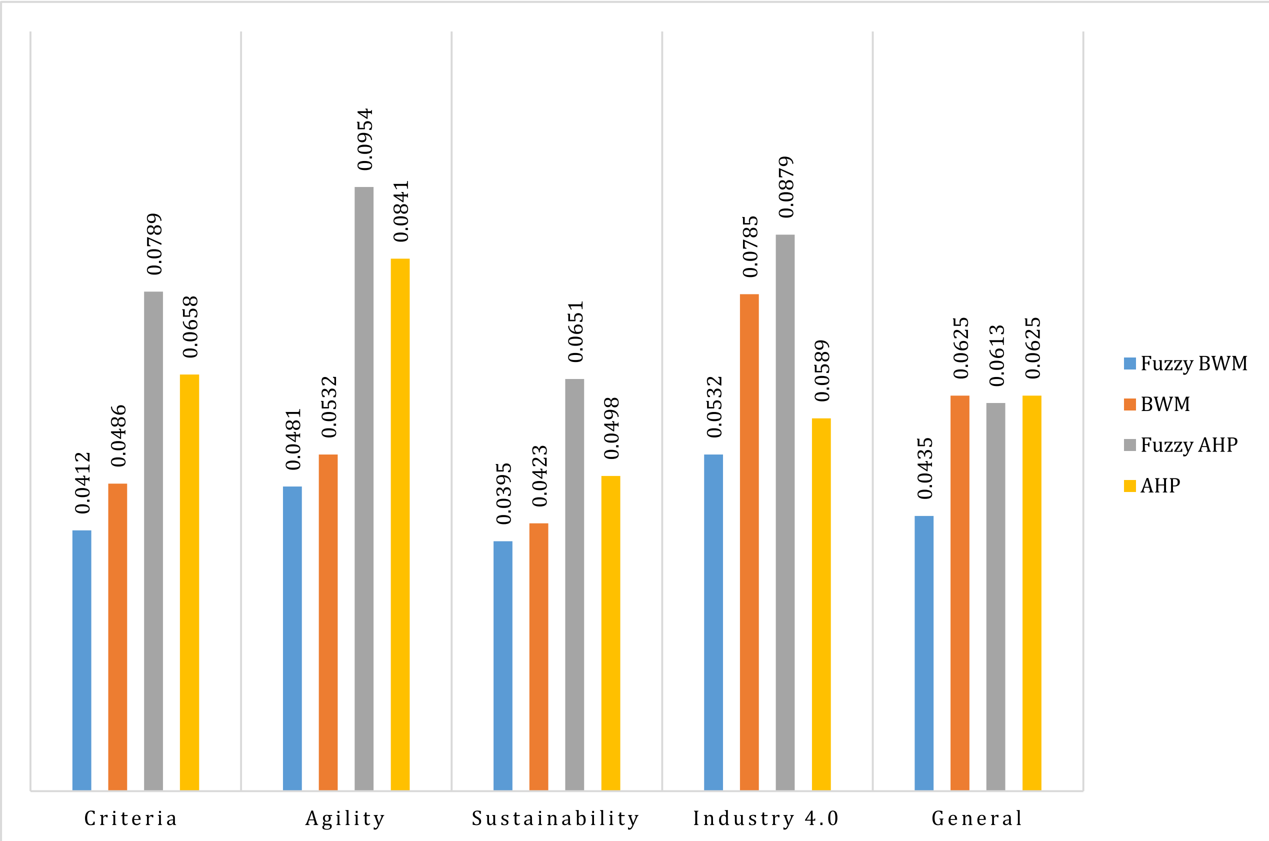

FIGURE 5. The CR metric achieved by different methods.

mislabeling of labels, allowing for the examination of the model's error magnitude and severity. As seen in Figure 6, the error in estimating labels is relatively low, and it is noteworthy that the types of errors are such that the differences between the labels compared to the correct estimate are not severe; for example, in none of the evaluations is the label very poor misestimated as good or very good, and very poor is necessarily misestimated as poor and, much less frequently, as average. This situation applies to other labels as well, indicating the suitable performance of the developed algorithm in estimating the performance labels of supply chain branches.

In addition to the confusion matrix, indicators such as Accuracy, Precision, Recall, and F1-score are used to estimate the model's accuracy. These mentioned indicators are calculated using equations (5)–(8) [18].

$$Accuracy=\frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i+FP_i} \tag{5}$$

$$Precision=\frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i+FN_i} \tag{6}$$

$$Recall=\frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i+FP_i} \tag{7}$$

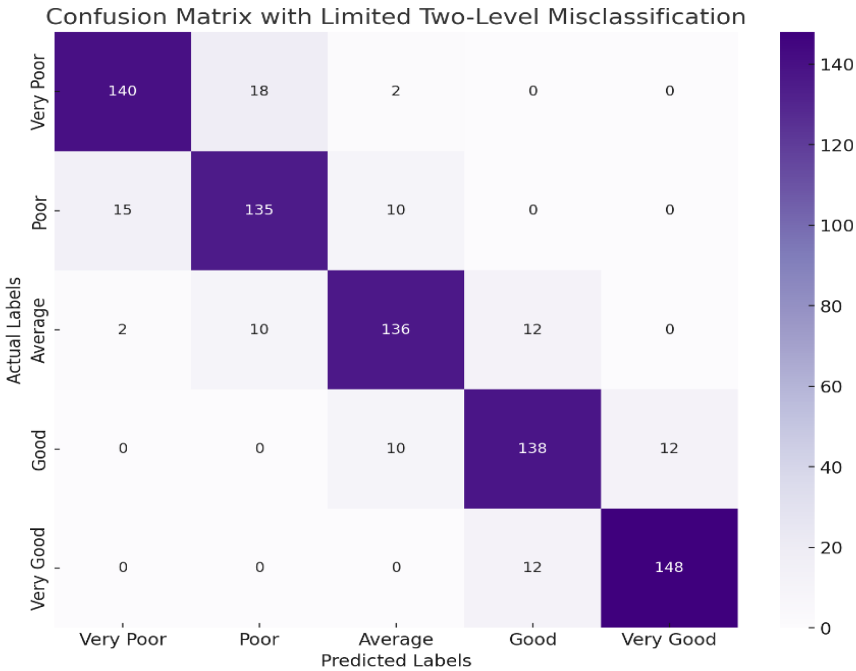

FIGURE 6. Confusion matrix in WANN algorithm.

$$F1\text{-}score = \frac{2 * (precision * recall)}{(precision + recall)}. \tag{8}$$

In the formulas mentioned, True Positive (TP_i): If the data actually has a P_i label and the predicted value shows the same. False Positive (FP_i): If the individual does not have a P_i label, but the prediction result displays another label.

In Figure 7, a comparison of model accuracy evaluation indicators in the WANN algorithm with simple ANN, as well as with Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN) algorithms, is presented. All the aforementioned algorithms belong to the category of classification algorithms, which can develop a supply chain performance evaluation model using the dataset provided in this paper. All the algorithms were developed using this paper's dataset. The aim of this section is to evaluate the performance of WANN in comparison to other algorithms in this field. The findings indicate that the accuracy of the WANN algorithm is better across all evaluation indicators compared to other algorithms.

4.5. Managerial insights

This study evaluates various branches of a dairy products company's supply chain using data-driven approaches. One of the central organization's concerns regarding the monthly performance evaluation of different branches is how to assess and compare them with each other. In this regard, the model developed in this study provides an approach that estimates the performance of supply chain branches by entering data related to the indicators, which can also be calculated intelligently.

Generally, performance evaluation approaches are often based on qualitative indicators or individual assessments, which can introduce errors due to various reasons and personal biases. This study presents a hybrid model that uses quantitative indicators for evaluating the performance of supply chain branches and employs the WANN machine learning algorithm for the evaluation, which is carried out without human intervention. This

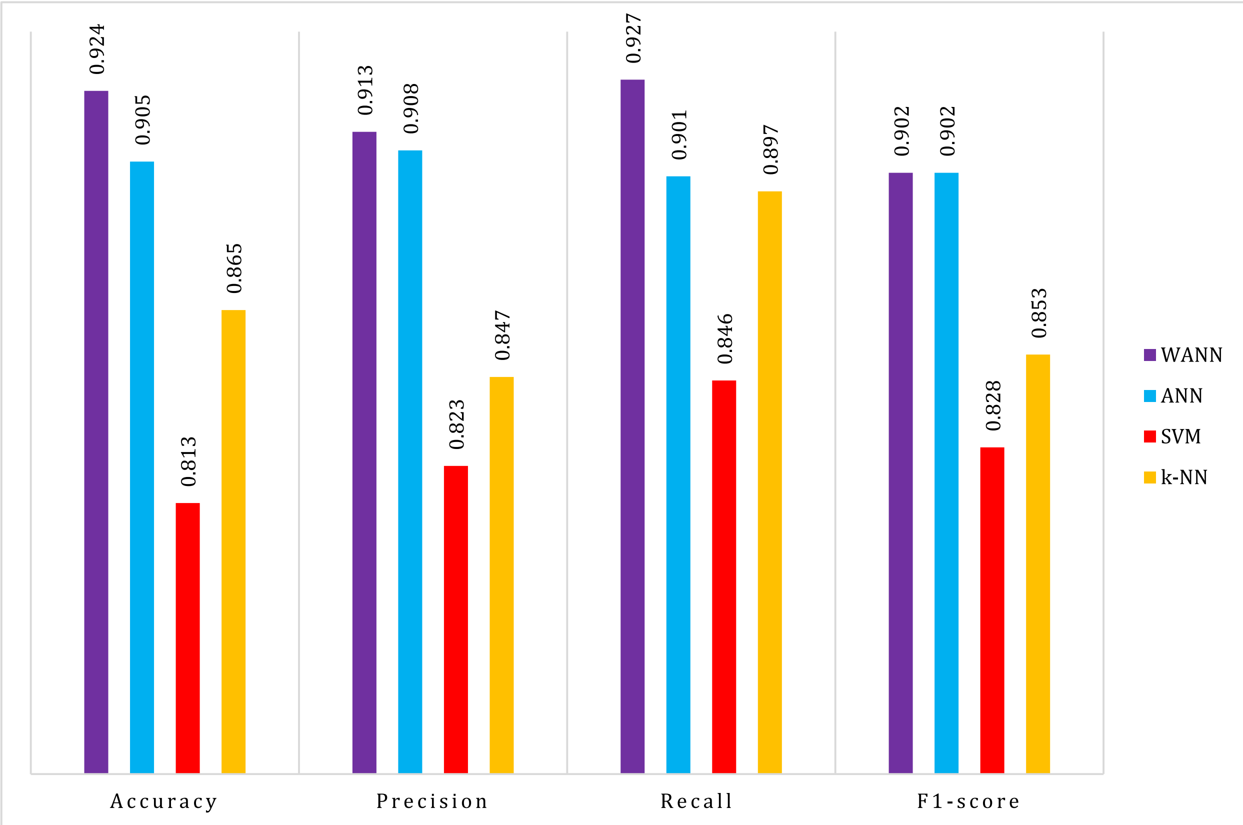

Figure 7. Algorithm performance comparison.

eliminates the influence of personal biases or evaluator errors in the performance assessment process. Therefore, organizations and company managers are always advised to develop all human-based evaluation structures intelligently and data-driven to avoid potential errors.

Another point to consider is the indicators used for evaluating supply chain performance. In the food industry, agility is crucial due to the importance of high speed in various parts of the supply chain to prevent spoilage and address other issues. Sustainability is important due to environmental concerns and the attention to social responsibilities, and the Industry 4.0 dimension is significant due to the need for organizations to move towards utilizing these technological infrastructures. This study has developed a model that considers sustainability, agility, and Industry 4.0 (digitalization) indicators alongside general indicators. This ensures a comprehensive performance evaluation of the units. In this context, managers are recommended to use new indicators and components in performance evaluation and can benefit from this study's model in similar industries.

From another perspective, the developed model is a hybrid approach where the weights of the evaluation indicators are calculated based on expert opinions, and then a model for evaluating supply chain units is developed using documented data and classification algorithm rules. The results indicate that the hybrid approach is more efficient than purely data-driven methods due to the uncertainties and errors present in the data. The use of hybrid approaches covers these errors and deficiencies. Another notable point is that in cases where data is scarce, expert opinions can be more effective. Therefore, it is recommended to use hybrid approaches and incorporate expert opinions when developing data-driven models in various organizational sectors.

5. Conclusions and outlooks

In today's world, performance evaluation within multi-level organizations has become a crucial issue. Organizations often evaluate the performance of various branches based on different components and intuitive approaches. In this study, a model has been developed for evaluating the performance of supply chain branches based on indicators of agility, sustainability, and Industry 4.0. In this regard, the metrics in this study can effectively help organizations evaluate the performance of their branches and have been identified in the categories of agility, sustainability, Industry 4.0 (digitization), and general metrics. The most important metrics identified in this study, according to experts in the dairy industry, include Data-driven, Marketing, Overhead costs, Delivery Timeframe, and Product Quality, considering a combination of traditional and modern metrics. The weight and importance of the evaluation metrics indicate that cost and quality have consistently been a focus for managers and organizations over the past few decades. However, it is noteworthy that digitization metrics and more advanced product marketing development have been added, which have changed compared to previous years. The main reason for this shift is the increased competition within supply chains.

The model developed in this study for evaluating the performance of supply chain branches utilizes hybrid data-driven approaches. This involves combining expert opinions for weighting the metrics and developing a data-driven model based on an artificial neural network, resulting in a model with high performance and accuracy. The findings of this study indicate that in today's world, recorded data are also subject to uncertainties and errors. Therefore, using hybrid approaches can provide better performance compared to purely data-driven or purely intuitive approaches. In this study, a hybrid method was developed where the weights of the evaluation metrics were calculated based on the opinions of organizational and research experts, but the evaluation was conducted using actual and documented organizational data. Consequently, this study suggests that due to the lack of extensive data from various dimensions of the subject, data-driven models should incorporate hybrid approaches by integrating expert opinions.

Furthermore, this study suggests that other algorithms and hybrid approaches be developed to enhance evaluation models, enabling more accurate and faster assessment of target organizations' performance. Explainable Artificial Intelligence (XAI) algorithms can also be used for better interpretation of the models. Additionally, other paradigms such as circular economy, resilience, and accountability can be considered in the evaluation metrics.

Data availability statement

Data available on request from the authors.

Author contribution statement

All authors contributed extensively to the work presented in this paper.

Informed consent

All authors have read and agreed to the published version of the manuscript.

References

[1] S. Aria, S.A. Torabi and S. Nayeri, A hybrid fuzzy decision-making approach to select the best online-taxis business. *Adv. Ind. Eng.* **54** (2020) 99–120.

[2] B. Esmaeilian, J. Sarkis, K. Lewis and S. Behdad, Blockchain for the future of sustainable supply chain management in Industry 4.0. *Resour. Conserv. Recycl.* **163** (2020) 105064.

[3] A. Fathi, B. Karimi and R.F. Saen, Sustainability assessment of supply chains by a novel robust two-stage network DEA model: A case study in the transport industry. *Soft Comput.* **26** (2022) 1–18.

[4] A.A. ForouzeshNejad, Leagile and sustainable supplier selection problem in the Industry 4.0 era: A case study of the medical devices using hybrid multi-criteria decision making tool. *Environ. Sci. Pollut. Res.* **30** (2023) 13418–13437.

[5] S. Guo and H. Zhao, Fuzzy best-worst multi-criteria decision-making method and its applications. *Knowl. Based Syst.* **121** (2017) 23–31.

[6] A.D. Guritno, M. Ushada, N.E. Kristanti, M.S. Dharmawati and N.A.S. Putro, Development of quality evaluation model for supply chain of capture fisheries in Southern Coast of Java. *Agric. Eng. Int. CIGR J.* **23** (2021).

[7] A. Gyarmathy, K. Peszynski and L. Young, Theoretical framework for a local, agile supply chain to create innovative product closer to end-user: Onshore-offshore debate. *Oper. Supply Chain Manag. Int. J.* **13** (2020) 108–122.

[8] U. Hasson, S.A. Nastase and A. Goldstein, Direct fit to nature: An evolutionary perspective on biological and artificial neural networks. *Neuron* **105** (2020) 416–434.

[9] A. Hosseini Dolatabad, J. Heidary Dahooie, J. Antucheviciene, M. Azari and S.H. Razavi Hajiagha, Supplier selection in the industry 4.0 era by using a fuzzy cognitive map and hesitant fuzzy linguistic VIKOR methodology. *Environ. Sci. Pollut. Res.* **30** (2023) 52923–52942.

[10] D. Ivanov and A. Dolgui, Viability of intertwined supply networks: Extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *Int. J. Prod. Res.* **58** (2020) 2904–2915.

[11] B. Javan-Molaei, R. Tavakkoli-Moghaddam, M. Ghanavati-Nejad and A. Asghari-Asl, A data-driven robust decision-making model for configuring a resilient and responsive relief supply chain under mixed uncertainty. *Ann. Oper. Res.* (2024) 1–38.

[12] R.T. Khameneh, M. Elyasi, O.Ö. Özener and A. Ekici, A non-clustered approach to platelet collection routing problem. *Comput. Oper. Res.* **160** (2023) 106366.

[13] M.M. Khan, I. Bashar, G.M. Minhaj, A.I. Wasi and N.U.I. Hossain, Resilient and sustainable supplier selection: An integration of SCOR 4.0 and machine learning approach. *Sustain. Resil. Infras.* **8** (2023) 1–17.

[14] M. Krstić, V. Elia, G.P. Agnusdei, F. De Leo, S. Tadić and P.P. Miglietta, Evaluation of the agri-food supply chain risks: The circular economy context. *Br. Food J.* **126** (2024) 113–133.

[15] S. Kusi-Sarpong, H. Gupta, S.A. Khan, C.J. Chiappetta Jabbour, S.T. Rehman and H. Kusi-Sarpong, Sustainable supplier selection based on Industry 4.0 initiatives within the context of circular economy implementation in supply chain operations. *Prod. Plan. Control* **34** (2023) 999–1019.

[16] B. Li, C. Delpha, D. Diallo and A. Migan-Dubois, Application of artificial neural networks to photovoltaic fault detection and diagnosis: A review. *Renew. Sustain. Energy Rev.* **138** (2021) 110512.

[17] S. Nayeri, M.A. Khoei, M.R. Rouhani-Tazangi, M. GhanavatiNejad, M. Rahmani and E.B. Tirkolaee, A data-driven model for sustainable and resilient supplier selection and order allocation problem in a responsive supply chain: A case study of healthcare system. *Eng. Appl. Artif. Intell.* **124** (2023) 106511.

[18] S. Nessari, M. Ghanavati-Nejad, F. Jolai, A. Bozorgi-Amiri and S. Rajabizadeh, A data-driven decision-making approach for evaluating the projects according to resilience, circular economy and Industry 4.0 dimension. *Eng. Appl. Artif. Intell.* **134** (2024) 108608.

[19] D. Oliveira-Dias, J. Moyano-Fuentes and J.M. Maqueira-Marín, Understanding the relationships between information technology and lean and agile supply chain strategies: A systematic literature review. *Ann. Oper. Res.* **312** (2022) 973–1005.

[20] Z. Pang, F. Niu and Z. O'Neill, Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons. *Renew. Energy* **156** (2020) 279–289.

[21] M. Qin, C.W. Su, M. Umar, O.R. Lobonţ and A.G. Manta, Are climate and geopolitics the challenges to sustainable development? Novel evidence from the global supply chain. *Econ. Anal. Policy* **77** (2023) 748–763.

[22] S. Rahimi, A. Hafezalkotob, S.M. Monavari, A. Hafezalkotob and R. Rahimi, Sustainable landfill site selection for municipal solid waste based on a hybrid decision-making approach: Fuzzy group BWM-MULTIMOORA-GIS. *J. Clean. Prod.* **248** (2020) 119186.

[23] A. Rasmussen, H. Sabic, S. Saha and I.E. Nielsen, Supplier selection for aerospace & defense industry through MCDM methods. *Clean. Eng. Technol.* **12** (2023) 100590.

[24] M. Razeghi, A. Hajinezhad, A. Naseri, Y. Noorollahi and S.F. Moosavian, Multi-criteria decision-making for selecting a solar farm location to supply energy to reverse osmosis devices and produce freshwater using GIS in Iran. *Sol. Energy* **253** (2023) 501–514.

[25] J. Rezaei, T. Nispeling, J. Sarkis and L. Tavasszy, A supplier selection life cycle approach integrating traditional and environmental criteria using the best worst method. *J. Clean. Prod.* **135** (2016) 577–588.

[26] O. Rostami, M. Tavakoli, A. Tajally and M. GhanavatiNejad, A goal programming-based fuzzy best–worst method for the viable supplier selection problem: A case study. *Soft Comput.* **27** (2023) 2827–2852.

[27] R.B. Sánchez-Flores, S.E. Cruz-Sotelo, S. Ojeda-Benitez and M.E. Ramírez-Barreto, Sustainable supply chain management—a literature review on emerging economies. *Sustainability* **12** (2020) 6972.

[28] M.S. Sangari, J. Razmi and S. Zolfaghari, Developing a practical evaluation framework for identifying critical factors to achieve supply chain agility. *Measurement* **62** (2015) 205–214.

[29] Z. Sazvar, M. Tavakoli, M. Ghanavati-Nejad and S. Nayeri, Sustainable-resilient supplier evaluation for high-consumption drugs during COVID-19 pandemic using a data-driven decision-making approach. *Scientia Iranica* (2022).

[30] Y. Shao, D. Barnes and C. Wu, Sustainable supplier selection and order allocation for multinational enterprises considering supply disruption in COVID-19 era. *Aust. J. Manag.* **48** (2022) 031289622110669.

[31] Y. Shen and K. Liao, An application of analytic hierarchy process and entropy weight method in food cold chain risk evaluation model. *Front. Psychol.* **13** (2022) 825696.

[32] S. Srhir, A. Jaegler and J.R. Montoya-Torres, Uncovering Industry 4.0 technology attributes in sustainable supply chain 4.0: A systematic literature review. *Bus. Strategy Environ.* **32** (2023) 4143–4166.

[33] M. Tavakoli, A. Tajally, M. Ghanavati-Nejad and F. Jolai, A Markovian-based fuzzy decision-making approach for the customer-based sustainable-resilient supplier selection problem. *Soft Comput.* **27** (2023) 1–32.

[34] O.F. Valilai and M. Sodachi, Inspiration of Industry 4.0 to enable a proactive sustainability assessment model through the supply chain. *Procedia Manuf.* **52** (2020) 356–362.

[35] L. Xin, S. Lang and A.R. Mishra, Evaluate the challenges of sustainable supply chain 4.0 implementation under the circular economy concept using new decision making approach. *Oper. Manag. Res.* **15** (2022) 1–20.

[36] P. You, S. Guo, H. Zhao and H. Zhao, Operation performance evaluation of power grid enterprise using a hybrid BWM-TOPSIS method. *Sustainability* **9** (2017) 2329.

[37] S.I. Zaman, S. Khan, S.A.A. Zaman and S.A. Khan, A grey decision-making trial and evaluation laboratory model for digital warehouse management in supply chain networks. *Decis. Anal. J.* **8** (2023) 100293.