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Modeling Livestock Procedures Toward Precision and Sustainable Livestock Farm in Era of Virtual Technologies: Lessons, Opportunities, Avenues of Digitization

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Abstract

Presently contemporary and virtual technologies that are being embraced by many businesses have a favorable influence. For instance, biometric sensors of the Internet of Things (IoT), artificial intelligence (AI), big data (BD), blockchain technology (BCT), and so on in livestock permit the real-time observation of the health and behavior of animals. Also, monitoring helps prevent deterioration, diagnose injuries, and stress, and sustain productivity. The collected data from biometric sensors is analyzed by using BD securing the processed information and making it transparent for partners using BCT. Achieving safety and security through collaborating human robots (cobots) Accordingly, these technologies turn traditional livestock into precision livestock farms (PrLFs). Currently, the concept of precision serves as the cornerstone for the advancement of sustainable and user-friendly livestock farm management in many nations as well as globally. Hence, the objective of this study is to embrace the concept of precision and illustrate its influence on livestock farms toward sustainability of livestock farm. These objectives consider catalysts for analyzing and evaluating the sustainability of livestock farms that embrace contemporary technologies in their operations and practices. Moreover, we are constructing an evaluation model for obtaining the most sustainable livestock farm through harassing Multi-Criteria Decision Making (MCDM) techniques where each technique is responsible for a certain function. For instance, CRiteria Importance Through Inter-criteria Correlation (CRITIC) is utilized for obtaining the criteria's weights and the combined compromise solution (CoCoSo) leverages the obtained weights from CRITIC for ranking the alternatives of livestock farms and recommends the most sustainable and worst alternative. The evaluation for alternatives is performed based on rating four main criteria related to sustainability's pillars and thirteen sub-criteria. Finally, the utilized MCDM techniques are working under the authority of Triangular Neutrosophic Sets (TrNSs) to bolster these techniques when handling incomplete information and perplexed situations.

Keywords: Precision Livestock, Sustainability; Triangular Neutrosophic Sets; MCDM; Contemporary Technologies.

1 | Introduction

The livestock sector has the potential to be a major force in the achievement of Sustainable Development Goals (SDGs)by assisting in the eradication of starvation and malnutrition [1]. Scholars in [2] demonstrated

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that raising livestock is a major global strategy to lower childhood wasting and stunting in children. Nonetheless, there are some risks to livestock farms' capacity to survive and then its sustainability. Livestock husbandry's carbon emissions [3] have become a critical problem that threatens the industry's ability to grow sustainably. Confirming that [4]where overindulgence in emissions of carbon intensifies the effects of global warming and declining ecological sustainability. That is why there is resource scarcity, health harm, economic stagnation, and harsh weather [5]. Given that [6] a large portion of the world's food security depends on cattle production, risks associated with climate change might become even more pressing.

In order to maintain sustainable livestock production [7], a climate response plan is required, as livestock crises brought on by climate change have the potential to reduce livestock farming and the quality of animal meals, resulting in a food crisis. In light of the climate catastrophe and the growing importance of global warming[8], by 2050 GHG reduction target for food security and a sustainable society is necessary.

Another factor that threatens livestock's sustainability is discussed in [9] where the long-term sustainability of livestock production systems—particularly those that generate meat and milk—as well as supply networks, commerce, and consumer purchasing habits have all been significantly impacted by COVID-19.

From the perspective of [10] Livestock producers and businesses must collaborate to embrace technologies as solutions that can help reduce greenhouse gas emissions and achieve carbon-neutral livestock to achieve these goals to make livestock sustainable environmental, economic, and social. In the same vein [11] demonstrated that the adoption of cutting-edge technologies like the Internet of Things (IoT), robots, artificial intelligence (AI), and so on has increased the efficiency of the livestock farming sector. Moreover, embracing the mentioned technologies in studies of [10], and [11] is a motivator for raising the concept of Precision livestock farming (PrLF). The intent of PLF exhibited in [12] as establish a management system that relies on real-time, integrated automated control and monitoring of animal welfare, health, and reproduction as well as the effects of livestock farming on the environment. On the other hand, utilizing and adopting industry 4.0 (Ind 4.0) [13] that permit real-time communication and cooperation between cyber-physical systems (CPSs) and people are facilitated by IoTs. Hence, PrLF is considered a defense for the sustainability of livestock framing against any hazards. For instance [14] pandemic of COVID-19 has resulted in serious secondary health issues for both humans and animals as well as economic damage, though social isolation and lockdowns are required to prevent and postpone the virus's spread. PrLF can avoid such hazards for the sustainability of livestock as illustrated in Figure 1.

Given the importance of embracing technologies for livestock to be PrLF and then sustainable. Therefore, evaluating livestock framing and its ability to survive and competitors is crucial. This issue is a catalyst for conducting this study to obtain the most sustainable livestock farm amongst the set of alternatives of livestock farms that embrace the PrLF in their operation.

To achieve the study's objectives, we are evaluating the sustainability of alternatives of livestock farms based on a set of criteria. For this reason, MCDM techniques have been harassed for analyzing alternatives based on the determined criteria due to the ability of these techniques to treat conflicting criteria. Accordingly, CRiteria Importance Through Inter-criteria Correlation (CRITIC) is utilized for generating criteria weights that leverage in Combined Compromise Solution (CoCoSo) for ranking alternatives of livestock farms and recommending the most sustainable livestock farm. These techniques are supported by Triangular Neutrosophic Sets (TrNSs) is type of uncertainty theory of Neutrosophic in situations characterized by ambiguity and when treated with incomplete information.

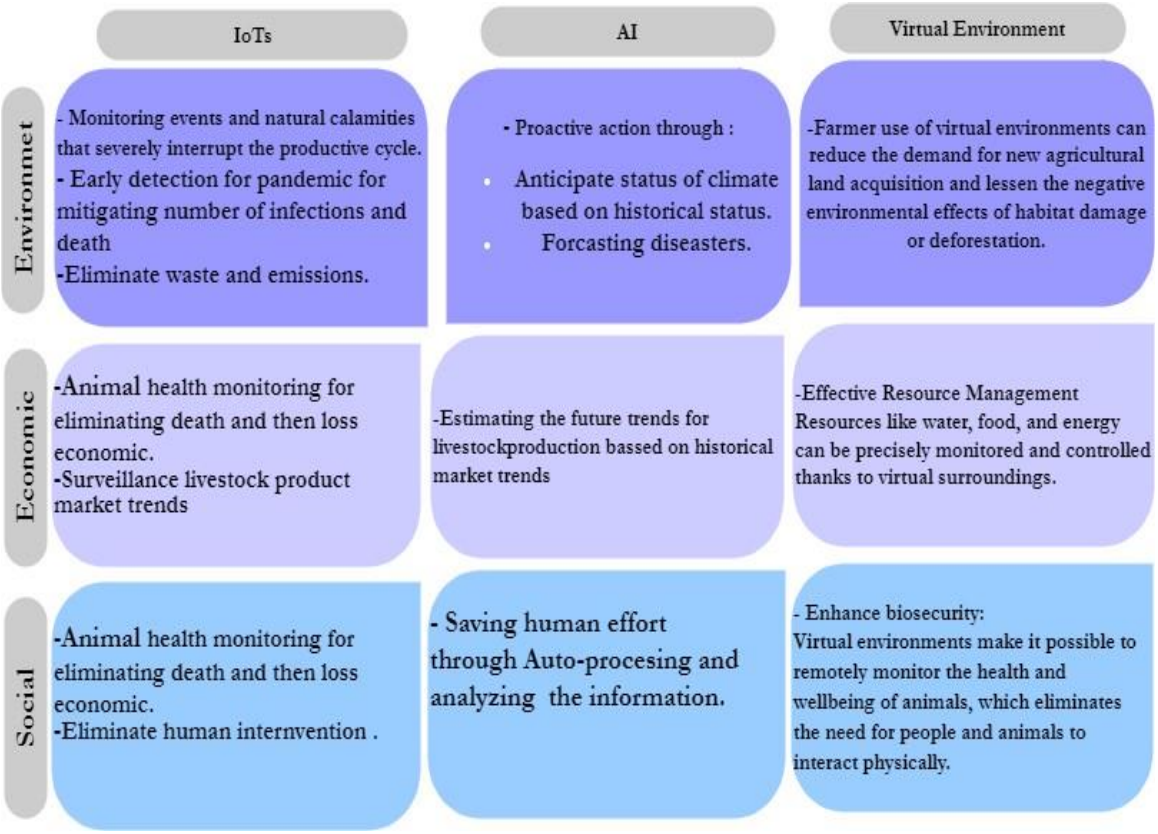

Figure 1. Technologies of precision livestock farming toward pillars of sustainability.

2 | Role of Contemporary Technologies for Precision and Sustainability of Livestock Farm

Various Digital Technologies like the Internet of Things (IoT), data, (DLT), Blockchain (BC), artificial intelligence (AI), machine learning (ML), Cloud Computing, Edge Computing, Fog Computing, and so on are used to monitor Animal health and drive more Sustainable livestock. With the help of these technologies, farm-to-fork traceability techniques can be strengthened, fraud concerns related to food safety can be better managed, animal production regulations can be followed, and culinary standards, streamlining processes, enabling commerce, and increasing customer awareness.

2.1 | Internet of Things (IoT

IoT are a sophisticated network of networked objects that always interact with one another and locations. It also includes data interchange and gathering to achieve group goals. Any physical objects connected over the internet, such as computers, cameras, smartphones, sensors, etc., are referred to as "things." IoT have become more adaptable and well-liked in the present era of technological advancement thanks to a variety of smart gadgets like sensors, smartphones, tablets, smart wristbands, and Radio Frequency Identification (RFID) [15]. IoT are a very promising technology that offers many creative ways to modernize cattle husbandry. It is believed IoT technology can revolutionize livestock farming systems by connecting livestock sensor data, particularly identifying animals who are located remotely from the farm, via the internet [16]. Important innovations in the last few years include machine-assisted milking, automated feeding, and increasing production efficiency through nutrition, instrumentation, and animal health monitoring [16]. The world's growing need for livestock products has made processing large amounts of data more difficult. Fortunately, IoTs can assist in the systematic and effective processing of data as well as its real-time availability, which greatly benefits users by providing them with access to basic information about input procurement, livestock management and production, livestock disease surveillance, and livestock product market trends. IoT are rapidly evolving into a crucial element of farming society, helping to expand and improve the livestock industry while providing improved solutions and increasing livestock output [15].

2.2 | Big Data

Big data describes collections of massive, complex, and diverse data that are difficult to store, handle, analyze, and visualize for use in other processes or outcomes. Big Data offers a multitude of techniques to tackle the challenge of processing and storing all the specifications and limitations needed to enable smart Livestock [17].

Big Data offers insights into the following domains [18] (i) animal behavior studies how an animal lives in its surroundings, (ii) animal welfare is concerned with the health and medical needs of animals, (iii) nutrition is about metabolic processes that consider an animal's diet,(iv) genetics regulates or controls genetic disease/irregularity and reproduction; and (v) species protection aims to prevent the extinction of a species. This technology is beneficial for stakeholders for (i) monitoring climate/weather, (ii) resilience to external factors influencing the farm, (iii) productivity monitoring for control over products and all surrounding processes, (iv) monitoring all individuals and their practices; and (v) for sustainability through monitoring the purpose of promoting sustainable food.

All the data generated spans all relevant sectors and offers comprehensive insights that should be fully utilized.

2.3 | Blockchain

A blockchain is a distributed, decentralized database of encrypted transactions in which every transaction generates a node. By use of consensus among participating parties, or peers, these nodes are arranged into records, or "blocks," and these blocks are connected to form a chain using distinct hash codes [19]. Distributed, transparent, immutable, and democratic are the four cornerstones of blockchain technology. This implies that in livestock husbandry, each animal on the farm needs to be given a special identifier. This special ID would be attached to the animal for the duration of its life to gather information about the farm or farms it had resided on, the mode of transportation used to get it from the farm to the slaughterhouse, the veterinary's examination of the animal at the slaughterhouse, the quality check that occurs after the animal is killed, the transportation of the meat product, and lastly the packager and retailer's details [20].

2.4 | Artificial Intelligence (AI)

AI technology plays a significant role in supporting smart farming practices that improve animal health and well-being while also producing positive economic results [21]. Traditional sectors, such as the dairy livestock export industry, are seeing paradigm upheavals due to the introduction of AI and advanced sensor technologies. AI and sensor technology-driven precision digital livestock farming provide novel answers to enduring problems in the dairy livestock export sector. These innovative solutions promise improved animal care, increased production, and more efficient supply chain operations by enabling real-time monitoring, proactive intervention, and data-driven decision-making [22].

2.4.1 | Machine learning (ML)

ML is a branch of artificial intelligence that uses algorithms for statistical prediction and inference [23] . With its ability to enable computer algorithms to gradually learn from sensor big data sets and adapt themselves accordingly, machine learning (ML) is becoming a more and more popular topic of study in precision cattle farming. This is because it renders human data analysts unnecessary [24]. ML approaches are widely applied in animal genetics research to genotype imputation, outlier identification, and phenotypic prediction based on genotypic information. ML has also been applied to picture analysis for body weight estimation, mastitis detection from automated milking technology on dairy farms, and microbiome health monitoring [23]. The welfare and production of dairy cattle could be enhanced by machine learning and big data analytics. They can be used to track and forecast the risk of mastitis and lameness in dairy cattle, two extremely important welfare concerns that can seriously impair milk output [25]. Two primary classifications of machine learning tasks are supervised and unsupervised learning. In the machine learning technique known as supervised learning, models are built using labeled data while being closely monitored by training data [15]. It indicates that certain data that has already been tagged or labeled with the right response—training data—is given to the computers to act as the supervisor and educate them on how to accurately forecast the output. Unsupervised learning is a machine learning approach that finds latent patterns in unlabeled data even while models are not supervised by training datasets [15].

2.5 | Cloud Computing

Using the internet, cloud computing is a technology that provides global access to shared pools of reconfigurable system resources that can be quickly and easily installed with little administrative work [26]. The adoption of the computing infrastructure-as-a-service architecture is inevitable as the livestock industry embraces the IoT paradigm. To employ computation and storage services, farmers would not need to own any infrastructure, especially in low-income areas. Livestock farmers will benefit greatly from these services (s) to the extent that they can pay with a token and connect to the cloud. Infrastructure as a service (IaaS), software as a service (SaaS), platform as a service (PaaS), container as a service (CaaS), and software as a service (SaaS) are examples of cloud-based technologies. Additionally, it enhances Quality of Service (QoS), data security, and application access efficiency. Furthermore, it makes operating models more easily accessible to livestock farmers [27].

2.6 | Edge Computing

A concept known as "edge computing" involves processing data close to where it originates. This method is a useful contribution to the domains of AI and IoT. It is easier to carry out important choices on time when data transfer latency is decreased [28]. Edge computing makes it possible to take quick action in livestock management when a cow exhibits unusual behavior. Edge Computing enables real-time monitoring of dairy animals and feed grain conditions. It guarantees the reliability and long-term viability of various production procedures. This prompt intervention may prevent health issues or improve the effectiveness of reproductive cycles. The lower latency also suggests that decisions are made more quickly, which is crucial for maintaining the welfare of animals [29].

2.7 | Fog Computing

Since farms are typically situated in isolated areas, there may be times when there is little to no Internet or network connectivity. It is best to process the data as much locally as possible in these unfavorable connectivity conditions and transfer the aggregated or partial outputs to the cloud via the Internet for further improved analytical results[30]. The purpose of fog computing is to guarantee that farmers can utilize the distributed computing paradigm and that it is operational. Additionally, fog computing will encourage the usage of near-user edge devices' capabilities to enhance computation. Farmers will have the open chance to collaborate on the numerous dispersed normal activities of regularly monitoring with sensors, even at strange hours, from a remote place [27].

Overall, the objective of this section is to exhibit the role of contemporary technologies in livestock to be precise toward achieving the resilience and sustainability of livestock in the market. Hence, evaluating the livestock farms that embrace these notions is vital and we attempted to cover this aspect through the following section of previous studies related to our study's cope.

3 | Comprehensive Overview of Prior Literature

This section showcases the various methodologies for evaluating livestock based on conducted surveys for earlier studies. For instance, the hazards associated with the livestock supply chain are ranked and evaluated using the analytical hierarchical process (AHP) [31] where The results also indicate that out of the seventeen risks "poor quality and undersupply of feed and fodder," "lack of proper waste disposal," and "absence of certification for the quality of animals" are the most prevalent. Geographical Information Systems GIS-MCDM hybrid with R-numbers in [32] to explore the selection of industrial livestock sites and select the optimal site. To generate sustainable solutions and alternatives based on economic, environmental, and social are three pillars of sustainability in [33], MCDM techniques are utilized for recommending sustainable and resilient livestock. Also, Neutrosophic theory collaborated with MCDM techniques [34] to minimize the inaccuracy in the disease diagnosis. The livestock feeding stuff is divided into categories by study of [35] as green fodder, subsidiary fodder, and concentrate feed These categories are prioritized by combining MCDM with plithogenic which can handle uncertain and ambiguous decision-making data. After that the combined techniques are compared with fuzzy CRITIC-MAIRCA and the findings indicated that plithogenic CRITIC-MAIRCA approach is extremely successful at generating a workable rating.

4 | Methodology of Evaluation Process: Proposed Model

The goal of this study is to determine whether and how stakeholders of livestock farms might use digital technologies (DTs) to optimize livestock and its operations to achieve PrLF and resilient and sustainable livestock farms. Moreover, in this study, the advantage of the Critic Method to determine the weights of criteria in MCDM problems is combined with CoCoSo to evaluate and rank Livestock alternatives. These techniques of MCDM are working under the authority of TrNSs through the following stages.

Stage 1: Data Collection

- Determining main criteria (CM) as {C1, C2, C3...CM} and sub- criteria (Cm-n) as {C1-1, C1-2…Cm-n}.
- Determining Alternatives in this regard include livestock-1, livestock-2, livestock-3 livestock-4, and livestock-5. For ease, the alternatives are denoted by the set T = {A1; A2; A3; A4; A5} respectively.
- Communicating with decision makers who contribute to the evaluation process and forming the panel.

The scale of TrNSs is utilized for placing linguistics terms and their corresponding value for each alternative based on criteria and sub-criteria.

Stage 2: Critic Based on TrNSs: Generating weights for criteria and their sub-criteria.

Importance The inter-criteria Correlation method is one of the weighting methods that determine weights for criteria with the support of TrNSs.

- **Weighting criteria**
- The Neutrosophic decision matrices are formed. It shows the performance of different alternatives with respect to various criteria.
- Convert the constructed decision matrices into de-neutrosophic matrices through Eq. (1).

$$\mathrm{Score}(\wp_{\mathrm{ij}}) = \frac{\mathrm{lij+mij+uij}}{9} * (2 + \mathrm{T} - \mathrm{I} - \mathrm{F}) \tag{1}$$

Where: i=1,2,3,…m; n=1,2,3,….. j; l, m, u refer to the lower, middle, and upper values and T, I, F refer to truth, indeterminacy and false respectively.

- Aggregate deneutrosophic matrices into a single decision matrix.

$$D\mu_{t_{ij}} = \frac{\sum_{j=1}^{N} \wp_{ij}}{Z} \tag{2}$$

Where: $\wp_{ij}$ refers to the value of the criterion in the matrix, and Z refers to the number of decision-makers.

- Normalizing aggregated matrix through the following equation:

$$x^*_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad i\text{=1,2, 3,…m; n=1,2,3,….. for benefit;} \tag{3}$$

$$x^*_{ij} = \frac{max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \quad i\text{=1,2, 3,…m; n=1,2,3,….. for non-benefit;} \tag{4}$$

Where: x^* is the normalized performance value of ith alternative on jth criterion.

- Calculate the standard deviation for each criterion per column as:

$$\sigma_j = \sqrt{\frac{1}{s-1} \sum_{j=1}^{s} (x_{ij} - x^*_j)^2} \tag{5}$$

Where: $x^*_j$is the mean score of criterion j, while s is the number of alternatives. whereas σj is the standard deviation of the jth criterion andr_{ij}' is the correlation coefficient between the two criteria.

- Correlation between criteria is computed according to Eq. (6).

$$g_{jk} = \sum_{i=1}^{n} (x_{ij} - x^*_j)(x_{ik} - x^*_k) / \sqrt{\sum_{i=1}^{m} (x_{ij} - x^*_j)^2 \sum_{i=1}^{m} ((x_{ik} - x^*_k)^2} \tag{6}$$

Where: g_{jk} is the correlation coefficient between jth and kth criteria.

- Quantity in relation to each criterion is calculated through Eq. (7).

$$C_j = \sigma_j \sum_{k=1}^{n} (1 - g_{jk}) \tag{7}$$

- The final weight is calculated by

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{8}$$

- **Weighting sub-criteria.**
- Following the previous steps of obtaining criteria weights for obtaining subcriteria weights

Stage 3: CoCoSo Based on TrNSs: Recommending the most sustainable livestock farm.

The combined Compromise Solution method depends on the relative distance of the alternative from the ideal one which gives the compromised solution of alternatives ranking.

- A normalized matrix of critic is utilized for generating weighted comparability sequence (Si) and power weight of comparability sequence (Pi) using Eqs. (9) and (10), respectively.

$$S_i = \sum_{j=1}^{n} (wj * x^*_{ij}) \tag{9}$$

where wj = final criteria weights by Critic method

$$P_i = \sum_{j=1}^{n} (x^*_{ij})^{wj} \tag{10}$$

- Based on S_i and P_i values, three appraisal score strategies are employed for ranking of alternatives which are calculated using Eqs. (11), (12), and (13), respectively.

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} P_i + S_i} \tag{11}$$

$$k_{ib} = \frac{S_i}{\min S_i} + \frac{P_i}{\min P_i} \tag{12}$$

$$k_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\lambda(\max S_i) + (1-\lambda)(\max P_i)} \qquad 0 \le \lambda \le 1 \tag{13}$$

where $\lambda = 0.5$ is usually chosen by the decision-maker, ranking can be done based on the k_{ia}, k_{ib}, k_{ic} (larger k acquires good rank preference), but it is recommended that the ranking obtained through all three appraisal scores should be in the highest agreement with each other.

- Determine the value of K_i using Eq. (14). Rank the alternatives based on K_i, and the alternative which has the highest value of K_i will acquire the first rank followed by others with decreasing K_i.

$$K_i = (k_{ia} k_{ib}\ k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \quad (14)$$

5 | Real Case Study

5.1 | Comprehensive Overview

We applied the constructed evaluation model of this study in a real case study of livestock farms to validate the accuracy of the constructed model. Herein, five livestock farms have contributed to this process embracing the technologies in their operations and practices for achieving Precision and sustainable livestock. The evaluation of five alternatives is conducted through a set of criteria and sub-criteria obtained from utilizing contemporary and virtual technologies. Thereby, four criteria are contributed to the rating also, and thirteen sub-criteria of contemporary and virtual technologies are contributed to the evaluation process as mentioned in Table 1.

Table 1. Criteria and associated points to be considered for evaluating livestock in terms of sustainability.

Main Criteria	Sub-Criteria	Description
Environmental Impact (C1)	Greenhouse gas emissions (C1-1)	Measurement and reduction of emissions such as methane and CO2 produced by livestock farming activities.
	Land use and biodiversity conservation (C1-2)	Conservation of natural habitats, preservation of biodiversity, and sustainable land management practices.
	Water usage and quality(C1-3)	Efficient use of water resources and prevention of contamination of water bodies through proper management practices.
Economic Viability (C2)	Cost-effectiveness(C2-1)	Ensuring profitability and financial sustainability of livestock operations while minimizing production costs.
	Market competitiveness (C2-2)	Ability to compete in the market by producing high-quality products that meet consumer demand while adhering to sustainability.
	Proactivity(C2-3)	Based on historical behaviors of the market, digital technologies have been utilized by farms to anticipate future events.
Social Responsibility (C3)	Animal welfare (C3-1)	Ensuring the health, comfort, and humane treatment of animals throughout their lives, from breeding to slaughter.
	Community engagement (C3-2)	Collaboration with local communities, stakeholders, and policymakers to address social needs, promote transparency, and foster trust.
	Labor conditions (C3-3)	Providing safe, fair, and healthy working conditions for farmworkers and employees involved in livestock farming operations.
Policy (C4)	Research and Development Funding (C4-1)	Allocation of funding for research and development initiatives aimed at advancing sustainable technologies, practices, and innovations in livestock farming.
	Incentive Programs (C4-2)	Participation in government-sponsored incentive programs that encourage the adoption of sustainable practices through subsidies, grants, tax incentives, or other financial mechanisms.
	Regulatory Compliance (C4-3)	Ensuring compliance with environmental regulations and standards related to livestock farming activities, including emissions, waste management, and land use.
	Stakeholder Engagement (C4-4)	Engagement with stakeholders such as government agencies, NGOs, community organizations, and industry associations to develop and implement policies that promote sustainability in livestock farming.

5.2 | Valuating Criteria and Sub-criteria: CRITIC-TrNSs

5.2.1 | Valuating Criteria

Members of the panel utilized the Triangular Neutrosophic scale for rating alternatives based on the determined criteria mentioned in Table 1.

- Five Neutrosophic decision matrices are constructed based on the members of the panel trough using a Triangular scale [36].
- Utilizing Eq. (1) to de-neutrosophic these matrices and aggregate them into an aggregated matrix using Eq. (2) as listed in Table 2.
- Table 3 illustrates the normalized matrix by employing Eqs. (3) and (4).
- Table 4 represents the Correlation between criteria is computed according to Eq. (6).
- Table 5 showcases the conflict degree of the main criteria. Figure 2 represents the final criteria's weights.

Table 2. Aggregate de-neutrosophic matrix of main criteria.

Alternatives	Criteria			
	C1 (-)	C2(+)	C3(+)	C4(+)
A1	2.9300	2.5267	2.2367	2.4133
A2	1.4267	3.2600	4.8167	3.6500
A3	3.9367	4.1667	4.2433	4.2967
A4	2.1000	4.4167	2.1433	2.2633
A5	0.6767	1.9100	3.7900	3.2533
max	3.9367	4.4167	4.8167	4.2967
min	0.6767	1.9100	2.1433	2.2633

Table 3. Normalize aggregate de-neutrosophic matrix of main criteria.

Alternatives	Criteria			
	C1 (-)	C2(+)	C3(+)	C4(+)
A1	0.3088	0.2460	0.0349	0.0738
A2	0.7699	0.5386	1.0000	0.6820
A3	0.0000	0.9003	0.7855	1.0000
A4	0.5634	1.0000	0.0000	0.0000
A5	1.0000	0.0000	0.6160	0.4869
σj	0.332	0.346	0.513	0.483

Table 4. Correlation coefficient values of the main criteria

Criteria	C1 (-)	C2(+)	C3(+)	C4(+)
C1	1.0000	-0.5508	0.1554	-0.2299
C2	-0.5508	1.0000	-0.0706	0.1147
C3	0.1554	-0.0706	1.0000	0.8980
C4	-0.2299	0.1147	0.8980	1.0000

Table 5. Conflict degree of the main criteria.

Criteria	C1 (-)	C2(+)	C3(+)	C4(+)
C1	0.000	1.551	0.845	1.230
C2	1.551	0.000	1.071	0.885
C3	0.845	1.071	0.000	0.102
C4	1.230	0.885	0.102	0.000

Table 6. Final weights of main criteria.

Criteria	σj	rij	Cj	Wj	Percent Wj
C1	0.332	3.625	1.205	0.266	26.64%
C2	0.346	3.507	1.213	0.268	26.81%
C3	0.513	2.017	1.035	0.229	22.88%
C4	0.483	2.217	1.071	0.237	23.67%
Sum			4.524	1.000	1.000

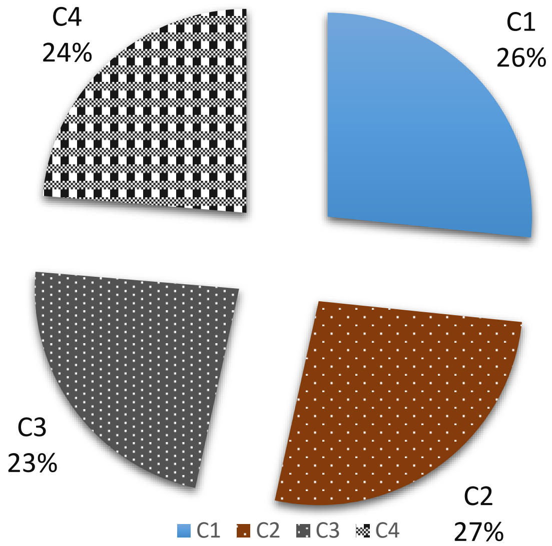

Figure 2. Final criteria weights.

5.2.2 | Valuating Sub-criteria

- The previous steps of obtaining the criteria's weights are repeated for obtaining the sub-criteria's weights.
- Tables 7, 12,17, and 22 showcase the aggregated matrix for sub-criteria of (C1, C2, C3, C4) respectively.
- The matrices of Tables 7, 12,17, and 22 are normalized and obtained in Tables 8,13,18, and 23 respectively.
- Correlation coefficient values of sub-criteria of Environmental are represented in Tables 9,14,19, and 24 respectively.
- Final weights for sub-criteria of each criterion are illustrated in Tables 11,16,21, and 26 according to Eq. (8).

Table 7. Aggregate de-neutrosophic matrix of sub-criteria of Environmental (C1).

Alternatives	Sub-Criteria		
	C1-1 (-)	C1-2 (-)	C1-3 (+)
A1	0.9367	2.3767	2.9600
A2	5.0400	2.9467	2.6133
A3	4.8167	4.8367	3.3700
A4	4.9533	2.6100	2.7600
A5	3.2167	1.9833	3.3800
max	5.0400	4.8367	3.3800
min	0.9367	1.9833	2.6133

Table 8. Normalize aggregate d de-neutrosophic matrix of sub-criteria of Environmental (C1).

Alternatives	Sub-Criteria		
	C1-1 (-)	C1-2 (-)	C1-3 (+)
A1	1.0000	0.8621	0.4522
A2	0.0000	0.6624	0.0000
A3	0.0544	0.0000	0.9870
A4	0.0211	0.7804	0.1913
A5	0.4444	1.0000	1.0000
σj	0.430	0.389	0.456

Table 9. Correlation coefficient values of sub-criteria of Environmental(C1).

Criteria	C1-1 (-)	C1-2 (-)	C1-3 (+)
C1-1	1.0000	0.476	0.197
C1-2	0.476	1.0000	-0.281
C1-3	0.197	-0.281	1.0000

Table 10. Conflict degree of sub-criteria of Environmental (C1).

Criteria	C1-1 (-)	C1-2 (-)	C1-3 (+)	sum
C1-1	0.000	0.524	0.803	1.327
C1-2	0.524	0.000	1.281	1.805
C1-3	0.803	1.281	0.000	2.084

Table 11. Final weights of sub-criteria of Environmental (C1).

weight	C1= 0.226					
criteria	σj	rij	Cj	Wj	Final Wj	Percent Wj
C1-1	0.430	1.327	0.570	0.257	0.05797	5.80%
C1-2	0.389	1.805	0.703	0.316	0.07146	7.15%
C1-3	0.456	2.084	0.950	0.427	0.09657	9.66%

Table 12. Aggregate de-neutrosophic matrix of sub-criteria of Economic (C2).

Alternatives	Sub-Criteria		
	C2-1 (-)	C2-2 (+)	C2-3 (+)
A1	2.6467	1.4533	1.9133
A2	4.0367	3.1100	3.7867
A3	3.7867	3.6767	2.5967
A4	3.7167	3.8033	2.2633
A5	3.2733	3.2600	3.7000
max	4.0367	3.8033	3.7867
min	2.6467	1.4533	1.9133

Table 13. Normalize aggregate deneutrosophic matrix of sub criteria of Economic (C2).

Alternatives	Sub-Criteria		
	C2-1 (-)	C2-2 (+)	C2-3 (+)
A1	1.0000	0.0000	0.0000
A2	0.0000	0.7050	1.0000
A3	0.1799	0.9461	0.3648
A4	0.2302	1.0000	0.1868
A5	0.5492	0.7688	0.9537
σj	0.393	0.401	0.453

Table 14. Correlation coefficient values of sub criteria of Economic (C2).

Criteria	C2-1 (-)	C2-2 (+)	C2-3 (+)
C2-1	1.000	-0.819	-0.490
C2-2	-0.819	1.000	0.353
C2-3	-0.490	0.353	1.000

Table 15. Conflict degree of sub-criteria of Economic (C2).

Criteria	C2-1 (-)	C2-2 (+)	C-23 (+)	sum
C2-1	0.000	1.819	1.490	3.309
C2-2	1.819	0.000	0.647	2.467
C2-3	1.490	0.647	0.000	2.137

Table 16. Final weights of sub-criteria of Economic(C2).

Weight	C2 = 0.268					
criteria	σj	rij	Cj	Wj	Final Wj	Percent Wj
C2-1	0.393	3.309	1.302	0.399	0.107	13.82%
C2-2	0.401	2.467	0.990	0.304	0.081	10.50%
C2-3	0.453	2.137	0.969	0.297	0.080	10.28%

Table 17. Aggregate de-neutrosophic matrix of sub-criteria of Social (C3).

Alternatives	Sub-Criteria		
	C3-1 (+)	C3-2 (+)	C3-3 (+)
A1	0.8667	3.3467	1.3400
A2	2.5600	2.7067	2.5867
A3	5.8467	3.6333	3.2700
A4	4.4233	1.2133	4.2367
A5	3.3600	3.9733	3.0267
max	5.8467	3.9733	4.2367
min	0.8667	1.2133	1.3400

Table 18. Normalize aggregate de-neutrosophic matrix of sub-criteria of Social (C3).

Alternatives	Sub-Criteria		
	C3-1 (+)	C3-2 (+)	C3-3 (+)
A1	1.0000	0.2271	0.0000
A2	0.6600	0.4589	0.4304
A3	0.0000	0.1232	0.6663
A4	0.2858	1.0000	1.0000
A5	0.4993	0.0000	0.5823
σj	0.378	0.395	0.365

Table 19. Correlation coefficient values of sub-criteria of Social (C3).

Criteria	C3-1 (+)	C3-2 (+)	C3-3 (+)
C3-1	1.0000	-0.116	-0.815
C3-2	-0.116	1.0000	0.539
C3-3	-0.815	0.539	1.0000

Table 20. Conflict degree of sub-criteria of Social (C3).

Criteria	C3-1 (+)	C3-2 (+)	C3-3 (+)	sum
C3-1	0.000	1.116	1.815	2.931
C3-2	1.116	0.000	0.461	1.577
C3-3	1.815	0.461	0.000	2.276

Table 21. Final weights of sub-criteria of Social (C3).

Weight	**C3 = 0.229**					
criteria	σj	rij	Cj	Wj	Final Wj	Percent Wj
C3-1	0.378	2.931	1.107	0.432	0.099	22.18%
C3-2	0.395	1.577	0.622	0.243	0.056	12.47%
C3-3	0.365	2.276	0.831	0.325	0.074	16.65%

Table 22. Aggregate de-neutrosophic matrix of sub-criteria of Policy(C4).

Alternatives	**Criteria**			
	C4-1 (+)	C4-2 (+)	C4-3 (+)	C4-4 (-)
A1	3.2067	3.0933	2.2133	3.9600
A2	3.9067	3.7600	3.7700	4.6200
A3	4.6733	2.0433	3.2133	5.4033
A4	1.7833	3.5833	4.3000	4.2800
A5	4.1633	4.1067	2.2400	2.3600
max	4.6733	4.1067	4.3000	5.4033
min	1.7833	2.0433	2.2133	2.3600

Table 23. Normalize aggregate de-neutrosophic matrix of sub-criteria of Policy (C4).

Alternatives	**Criteria**			
	C4-1 (+)	C4-2 (+)	C4-3 (+)	C4-4 (-)
A1	0.4925	0.5089	0.0000	0.4743
A2	0.4544	0.8320	0.7460	0.2574
A3	1.0000	0.0000	0.4792	0.0000
A4	0.0000	0.7464	1.0000	0.3691
A5	0.8235	1.0000	0.0128	1.0000
σj	0.385	0.388	0.443	0.369

Table 24. Correlation coefficient values of sub-criteria of Policy (C4).

Criteria	**C4-1 (+)**	**C4-2 (+)**	**C4-3 (+)**	**C4-4 (-)**
C4-1	1.000	-0.433	-0.603	0.018
C4-2	-0.433	1.000	-0.003	0.758
C4-3	-0.603	-0.003	1.000	-0.560
C4-4	0.018	0.758	-0.560	1.000

Table 25. conflict degree of sub-criteria of Policy (C4).

Criteria	**C4-1 (+)**	**C4-2 (+)**	**C4-3 (+)**	**C4-4 (-)**	**sum**
C4-1	0.000	1.433	1.603	0.982	4.018
C4-2	1.433	0.000	1.003	0.242	2.678
C4-3	1.603	1.003	0.000	1.560	4.167
C4-4	0.982	0.242	1.560	0.000	2.785

Table 26. Final weights of sub-criteria of Policy.

Weight	**C4 = .237**					
criteria	σj	rij	Cj	Wj	final w	Percent Wj
C4-1	0.385	4.018	1.546	0.283	0.0671	28.33%
C4-2	0.388	2.678	1.039	0.190	0.0451	19.03%
C4-3	0.443	4.167	1.845	0.338	0.0801	33.81%
C44	0.369	2.785	1.028	0.188	0.0446	18.83%

5.3 | Ranking Alternatives using the CoCoSo-TrNSs Method

- Normalized decision matrix of CRITIC and illustrated in Table 27 to generate a weighted decision matrix as in Table 28 based on Eq. (9).
- Table 29 represents the weight comparability sequence based on Eq. (10).
- The final ranking of alternatives is represented in Table 30. According to Figure 3, A2 is the most sustainable livestock farm otherwise, A1 is the worst alternative.

Table 27. Normalize aggregate de-neutrosophic matrix of Main criteria.

	C1 (-)	C2 (+)	C3 (+)	C4 (+)
Weight	0.2664	0.2681	0.2288	0.2367
A1	0.3088	0.2460	0.0349	0.0738
A2	0.7699	0.5386	1.0000	0.6820
A3	0.0000	0.9003	0.7855	1.0000
A4	0.5634	1.0000	0.0000	0.0000
A5	1.0000	0.0000	0.6160	0.4869

Table 28. Weighted normalized decision matrix (Si = Wj * Rij) of main criteria.

	C1 (-)	C2 (+)	C3 (+)	C4 (+)	Sum
A1	0.0822	0.0660	0.0080	0.0175	0.1737
A2	0.2051	0.1444	0.2288	0.1614	0.7397
A3	0.0000	0.2414	0.1797	0.2367	0.6578
A4	0.1501	0.2681	0.0000	0.0000	0.4182
A5	0.2664	0.0000	0.1409	0.1153	0.5225

Table 29. Weight-multiplied comparable sequence (Pi = Rij^Wij) of main criteria.

	C1 (-)	C2 (+)	C3 (+)	C4 (+)	Sum
A1	0.7313	0.6866	0.4641	0.5395	2.4215
A2	0.9327	0.8471	1.0000	0.9134	3.6932
A3	0.0000	0.9722	0.9463	1.0000	2.9185
A4	0.8583	1.0000	0.0000	0.0000	1.8583
A5	1.0000	0.0000	0.8951	0.8433	2.7384

Table 30. Final ranking of the alternatives Ki of main criteria.

	Si	Pi	Kia	Kib	Kic	Ki	Rank
A1	0.1737	2.4215	0.1608	2.3031	0.5854	2.4665	5
A2	0.7397	3.6932	0.2746	6.2469	1.0000	4.4665	1
A3	0.6578	2.9185	0.2216	5.3585	0.8068	3.9843	2
A4	0.4182	1.8583	0.1410	3.4081	0.5135	2.9499	4
A5	0.5225	2.7384	0.2020	4.4825	0.7356	3.5633	3
sum	2.5119	13.6299					
min	0.1737	1.8583					
max	0.7397	3.6932					

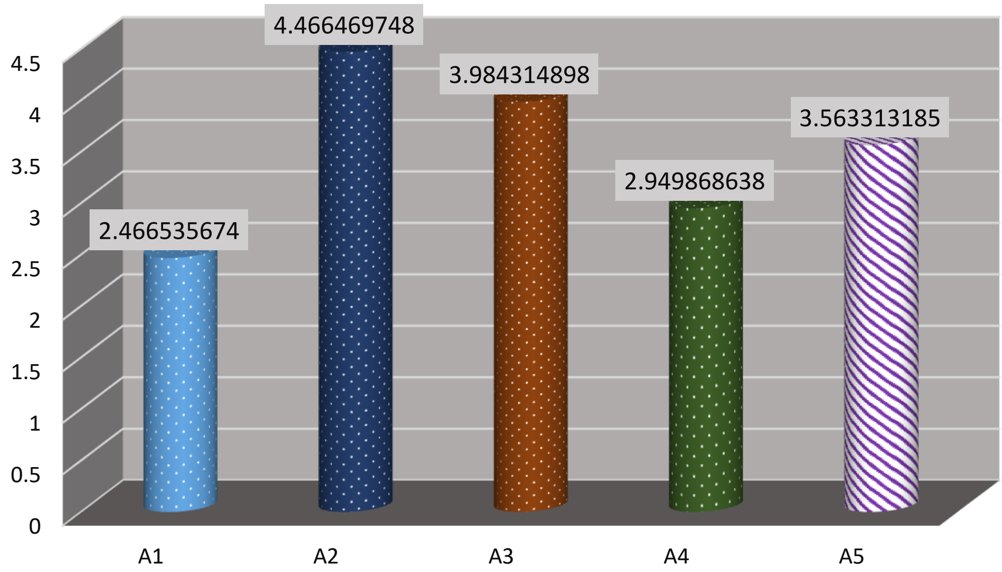

Figure 3. Ranking of livestock farms alternatives.

6 | Conclusions

After examining the many instruments and methods, it is reasonable to conclude that, in spite of numerous obstacles, the irrigation industry has developed a number of excellent technologies that have the potential to completely transform livestock in the future.

Contemporary technologies, such as smartphones, high-speed internet, and virtual technologies are already a part of our everyday lives. Currently, computers and smartphones are used by over half of the world's population to access the internet. Numerous nations worldwide have already adopted the use of cell phones for real-time alerts on various farm situations. In the days to come, modern digital technology will significantly increase productivity and efficiency in livestock and agricultural operations. In livestock production systems, the use of digital technologies has become increasingly important for comprehensive farm monitoring, mitigation of the dynamics and effects of climate change, animal disease surveillance, stopping the spread of livestock diseases, and being ready for pandemic emergencies. However, the livestock industry must ensure global food safety and reduce greenhouse gas emissions, among other issues. Sustainable production must receive more attention due to the sharp rise in demand for animal products. Decision-makers can create suitable sustainable production plans with the use of appropriate decision support systems.

Accordingly, this study attempted to examine livestock farms that embrace contemporary and virtual technologies for the precision and sustainability of livestock. This is a catalyst for constructing the evaluation model for analyzing the sustainability of these livestock farms according to sustainability's pillars which handle as criteria and its sub-criteria. This model was constructed based on collaboration between MCDM techniques and uncertainty theory especially, TrNSs.

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Author Contribution

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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