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ADM: Appraiser Decision Model for Empowering Industry 5.0-Driven Manufacturers toward Sustainability and Optimization: A Case Study

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Abstract: Whilst it was thought that Industry 4.0 (I 4.0) would support sustainable growth, it overlooked or misinterpreted many current sustainability issues, which gave rise to the Industry 5.0 (I 5.0) agenda. Such a revolution facilitates sustainable development through its three dimensions. Therefore I 5.0 promotes more effective management of business environment as supply chain resources. Although artificial intelligence (AI) and big data analytics (BDA) are becoming more well-liked in the context of supply chains, research to this day is fragmented into research streams that are mostly determined by the publishing outlet. This study appraises the ability of these techniques in manufacturing enterprises toward sustainability based on a set of criteria. Hence, we identified the criteria which related to AI and BDA. The various techniques as entropy and weighted sum models of multi-criteria decision-making (MCDM) techniques are working under the authority of single values neutrosophic sets (SVNSs) to enhance and boost these techniques in uncertain situations. The constructed appraiser decision model (ADM) is applied to real enterprises to validate this model.

Keywords: Industry 5.0; Artificial Intelligence; Big Data Analytics; Sustainability; Single Values Neutrosophic Sets.

1. Introduction

Shocks from the outside world go beyond our prior experiences and have major repercussions, which might change the competitive environment in which firms compete. The pandemic caused by the COVID-19 virus has been described as a shock, and since it first appeared, it has been responsible for a considerable number of fatalities [1]. We have recently been witness to a variety of negative repercussions and company failures within the realm of commerce. Some examples of these include layoffs, firm closures, and bankruptcies. These effects were, to a significant degree, the result of the adoption of needed social distancing measures to reduce the transmission of the virus, which had a severe influence on the profitability and sustainability of various enterprises [2].

A significant aspect of this external shock is that there will be a significant increase in the amount of uncertainty that exists within the framework of operations and supply chains in particular. This has, in many instances, been noticed as a result of the widespread broadcast of fake news, which has resulted in additional disruption for companies and day-to-day life, to the extent that it has led to what has been referred to as an "infodemic," which is spreading via internet and mainstream media. This information epidemic has influenced consumer behavior, in which customers have resorted to panic purchasing and stockpiling of medical, cleaning, and non-perishable goods, driven by the worry that products may become unavailable. It should not come as a surprise that this sudden shift in consumer behavior has, in turn, resulted in disruptions in the supply chain. This is because companies are attempting to alter their supply chain and operations in order to deal with and foresee the shift in demand [3].

Because, ultimately, interruptions are perceived as possible hazards that need to be foreseen and managed against, risk management is generally considered as a lens through which such disruptions are viewed when viewed from the standpoint of operations [4]. To be more specific, in terms of the repercussions that are caused by such disinformation and media hype, supply chain experts are expected to balance the risk of prospective stock-outs against the risk of keeping supplies of the product. In point of fact, subsequent studies have shown that the "bullwhip effect," which was caused by the spread of false information about Covid-19, swiftly led to an excess of inventory, hoarding, and significant problems with the management of inventories.

Businesses generally develop business continuity plans in addition to risk management methods as a means of mitigating the effects of interruptions in order to respond to issues of this kind. The deployment of vendor-managed inventory contractual agreements and the creation of leagile supply chains that boost the performance of the company in spite of uncertainties are two typical concrete techniques that serve as a precaution against such risks and are examples of typical risk mitigation measures. However, research has demonstrated that new technologies, such as artificial intelligence and corporate data analytics among others, are essential to ensuring the continuation of a firm, particularly in the face of external shocks. These days, supply chains are made better by sensors and actuators like RFIDs, GPS and POS, tags, and other smart devices. Since all of these things transmit and receive data, the Internet of Things has the potential to be an avenue via which accurate predictions may be made.

To this day, there is an ever-expanding interest in the usage and application of artificial intelligence (AI) and big data analytics (BDA) for risk management and establishing and sustaining resilience in supply chains. This interest can be seen in both the public and private sectors [5]. In spite of considerable curiosity, there are still certain areas that aren't completely understood. In a recent extensive assessment of supply chain resilience, the emphasis was on research carried out over the previous ten years. The study went into depth on the many kinds of disruptions, as well as their effect on the supply chain and recovery techniques for reducing them, while technology was looked at on a very abstract level. Other studies have concentrated on determining and categorizing the many AI approaches that are used for risk management, as well as assessing the various AI strategies that are employed as components of supply chain resilience.

This study is being driven by the overall research questions:

RQ1: What is the impact of AI and BDA on achieving a sustainable and resilient supply chain?

The answer to the previous question is in the following research question.

RQ2: What are the influenced criteria related to embracing AI and BDA in supply chain (SC) to gain competitive advantages toward sustainability?

RQ3: What are appraiser methods which volunteer for appraising enterprises based on influenced criteria extracted from embracing AI and BDA techniques?

2. Earlier Studies Related to our Scope

Herein, we exhibit various perspectives through conducting survey for previous studies which rely on embrace digital technologies in manufacturers' SC toward sustainability and to be resilience manufacturers.

2.1 Digital Technologies: Industry 5.0 a Paradigm

From perspective of [6] the focus on a human-centric approach, technological integration, cross-sector collaboration, and a shared goal of using technology for a better future have all been key inspirations for Industry 5.0 (I 5.0), which has drawn heavily from Society 5.0. in same vein [7] argued that in order to advance industrial productivity and socio-environmental values, I 5.0 should expand on several aspects of I 4.0, such as the widespread adoption of disruptive technical breakthroughs.

According to prior studies, I 5.0 aims focus on set of principles. For instance, [8] where I 5.0 focus on human-centricity through striking a balance between the use of digital technology to specifically adapt corporate operations to the demands of employees and the adaptation of human resources to the digitalization of society. This value aim suggests that rather than the opposite, digital technology should benefit society. Another principle entailed in circularity in [9] through embracing techniques as AI, digital twin (DT), BDA, etc. which already have the ability to encourage resource efficiency, reduce waste, make it easier to integrate greener energy, and promote cleaner manufacturing facilities.

Hence, we focused on studying the extent influence of embracing technologies of I 5.0 in manufacturing process and operation toward sustainable and resilience manufacturer.

2.2 *Sustainable Manufacturer Based on Industry 5.0*

Technologies of I 5.0 are contributing to achieve sustainability of manufacturer through covering various directions as mentioned in [10] and exhibits in Figure 1.

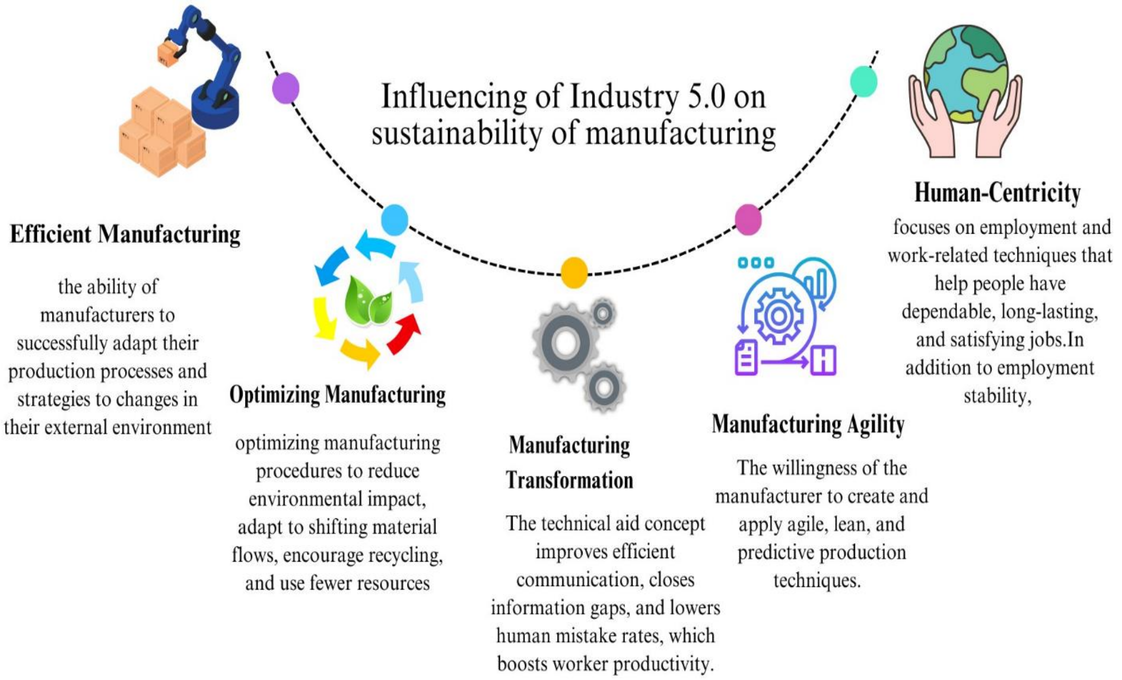

Figure 1. Role of Industry 5.0 on sustainability of manufacturing.

According to the survey conducted, appraising process for manufacturing's sustainability is vital. This process is conducting for manufacturers which embrace the notion of I 5.0 technologies in its chain whether inside and outside partners also, in its operations.

Herein, we focus on provide suitable methodology to appraise these manufacturers. Therefore, we constructed appraiser model in next section for making suitable decision for determining the most sustainable digital manufacturer. In this study, multi-criteria decision-making (MCDM) techniques have been volunteered under authority of uncertainty theory (i.e., neutrosophic) to appraise the alternatives of digital manufacturers and recommend optimal one to be sustainable digital manufacturers.

3. Appraisal Decision Model

Herein, we showcase methodology for appraising the manufacturers which embrace BDA-AI techniques whether inside or outside its chain. The appraisal process has been conducted for nominees of enterprises based on a set of criteria. Whereas the appraisal of enterprises is influenced by several direct and indirect factors, just as with a typical decision-making problem. Thereby, MCDM techniques are adopted and bolstered by uncertainty theory referred to neutrosophic theory to bolster MCDM techniques' capacity to cope with ambiguous situations and in complete data Process. Hence, this study mingles SVNSs as subset of neutrosophic theory with the Best Worst Method (BWM) - the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) as techniques of MCDM to generate ADM.

Consequently, the appraisal process in this study divides into set of stages:

Stage 1: *Insightful survey***.**

This stage entails the vital data that is collected through various methods such as field expeditions and conducted questionnaires for enterprises.

Firstly, we identify the most influential criteria based on prior studies.

Secondly, we prepared questionnaires in order to rate the identified criteria via managers and experts who related to our search scope.

Stage 2: *Calculation identified criteria's weights.*

Valuation of the identified criteria is an important stage and achieve through calculating criteria's weights. Herein, we are employing entropy technique to work under SVNSs as branch of neutrosophic theory for generating criteria's weights through following set of steps:

- Different neutrosophic decision matrices have been constructed based on preferences for each member of panel based on scale is listed in [11].
- These neutrosophic matrices are transforming into crisp matrices through employing Eq. (1).

$$\boldsymbol{s}(\mathrm{Q_{ij}}) = \frac{(2+\mathrm{Tr}-\mathrm{Fl}-\mathrm{Id})}{3} \tag{1}$$

  Where Tr, Fl, Id refers to truth, false, and indeterminacy respectively.
- These matrices are volunteering Eq. (2) to aggregate it into single decision matrix.

$$\mathrm{Y_{ij}} = \frac{(\sum_{j=1}^{N}\mathrm{Q_{ij}})}{\mathrm{N}} \tag{2}$$

  Where Q_{ij} refers to value of criterion in matrix, N refers to number of decision makers.
- Eq. (3) is utilized to normalize the aggregated decision matrix.

$$\mathrm{Norm}_{\mathrm{ij}=}\frac{\mathrm{y_{ij}}}{\sum_{j=1}^{m}\mathrm{y_{ij}}} \tag{3}$$

  Where $\sum_{j=1}^{m}\mathrm{y_{ij}}$ represents sum of each criterion in aggregated matrix per column.
- We are computing entropy based on Eq. (4).

$$\mathrm{e}_{\mathrm{j}=-\mathrm{h}\sum_{i=1}^{m}\mathrm{Norm_{ij}}} \ln \mathrm{Norm_{ij}} \tag{4}$$

$$h = \frac{1}{\ln(m)} \tag{5}$$

  M refers to number of alternatives.
- Compute weight vectors through employing Eq. (6).

$$\mathrm{w_j} = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)} \tag{6}$$

Stage 3: *Recommending optimal digital manufacturer.*

In this stage, we are merging weighted sum model (WSM) with SVNSs for achieving the purpose of this stage through recommending the optimal digital manufacturer. So, we follow set of steps for achieving this purpose.

- The aggregated decision matrix which is generated for previous stage is normalized according to following Eqs.

$$Norm_{Agg\_matij} = \frac{y_{ij}}{sum(y_{ij})} \quad , For\ Benficial\ key\ indicators \tag{7}$$

$$Z = \frac{1}{y_{Ij}} \tag{8}$$

$$Norm_{Agg\_matij} = \frac{Z}{sum(Z)} \quad , For\ Non-Benficial\ key\ indicators \tag{9}$$

Where:

y_{ij} indicates to each element in the aggregated matrix.

- The obtained key indicators' weights of entropy technique are applied in the following Eq. (10) to generate weighted matrix.

$$\mathrm{w\_matrix}_{ij} = \mathrm{weight}_i * \mathrm{Norm}_{\mathrm{Agg}_{\mathrm{matij}}} \tag{10}$$

Where:

$\mathrm{w\_matrix}_{ij}$ is weighted decision matrix.

- Utilizing Eq. (11) contributes to calculate global score. Based on values of $V(w\_matrix_{ij})$, ranking process for alternatives of perform and obtain optimal and worst manufacturer.

$$V(w\_matrix_{ij}) = \sum_{j=1}^{n} w\_matrix_{ij} \tag{11}$$

Where:

$V(w\_matrix_{ij})$ is global score values.

4. Empirical case study

We are applying our constructed ADM on real case study to ensure its validity. We communicated with manufacturing enterprises that related and embraced our study's notion. These manufacturing enterprises are in Egypt with different activities. The first manufacturing enterprise (ME1) that Medical and prosthetic devices, the second manufacturing enterprise (ME2) produces textile products, the third manufacturing enterprise (ME3) Produces electrical appliances and the manufacturing enterprise (ME4) is responsible for cable production.
We applied the mentioned stages of ADM to these enterprises manufacturing as follows:
Firstly, we identified the most influenced criteria which related to AI and BDA techniques toward the sustainability of these manufacturing. These criteria are summarized in the following Table 1 based on the study of [12].

Table 1. Influenced Criteria based on utilization of Big Data Analytics and Artificial Intelligence.

Criteria	Description
Proactivity (C_1)	Enterprises can use real-time crucial information made available by BDA to take corrective action.
Enhancing manufacturer performance (C_2)	The ability of AI to process information may be used to enhance and improve the manufacturing process [13].
Transparency (C_3)	All manufacturer's partners in its chain have ability for accessing to information [14].
Accurate forecasting(C_4)	Applying various AI techniques for analyzing real-time and historical data to forecast future behavior.
Vicinity to clients and suppliers (C_5)	Using agent-based simulation, AI techniques are being used to manage urban freight transportation [15].

After that, decision makers are contributing to rate the four alternatives based on the identified criteria based on scale in Ref [11].
Secondly, Entropy is utilized with support of SVNSs to generate vector of criteria's weights through applying several of equations are listed in following steps.
Step 1: Three neutrosophic decision matrices are created based on preferences for three decision makers.

Step 2: The constructed neutrosophic decision matrices transformed into deneutrosophic decision matrices based on Eq. (1).
Step 3: We aggregated these matrices into single deneutrosopic decision matrix through Eq. (2) as listed in Table 2.
Step 4: We are employing Eq. (3) to normalize the aggregated decision matrix to generate Table 3.
Step 5: We calculate entropy (e_j) through utilizing Eq. (4) to generate Table 4 and vector weight's criteria are produced in Figure 2. According to this Figure we noticed that C_1 is the highest criterion with highest value of weight followed by C_5 while C_2 is least one.

Table 2. Aggregated decision matrix.

	C_1	C_2	C_3	C_4	C_5
ME_1	0.6111	0.2611	0.8056	0.5389	0.6667
ME_2	0.5222	0.5000	0.7500	0.1611	0.7611
ME_3	0.6389	0.7389	0.4333	0.5944	0.4278
ME_4	0.6000	0.5222	0.3667	0.6333	0.5611

Table 3. Normalized decision matrix based on entropy-SVNSs.

	C_1	C_2	C_3	C_4	C_5
ME_1	0.2576	0.1291	0.3420	0.2795	0.2759
ME_2	0.2201	0.2473	0.3184	0.0836	0.3149
ME_3	0.2693	0.3654	0.1840	0.3084	0.1770
ME_4	0.2529	0.2582	0.1557	0.3285	0.2322

Table 4. Calculation of entropy.

	C_1	C_2	C_3	C_4	C_5
ME_1	-0.3494	-0.2643	-0.3669	-0.3563	-0.3553
ME_2	-0.3332	-0.3455	-0.3644	-0.2074	-0.3639
ME_3	-0.3533	-0.3679	-0.3115	-0.3628	-0.3065
ME_4	-0.3477	-0.3496	-0.2895	-0.3657	-0.3390
$\sum_{i=1}^{m} \mathbf{Norm_{ij}}$	-1.3836	-1.3273	-1.3323	-1.2922	-1.3647
$-h\sum_{i=1}^{m} \mathbf{Norm_{ij}\ ln\,Norm_{ij}}$	0.3459	0.3318	0.3331	0.3231	0.3412

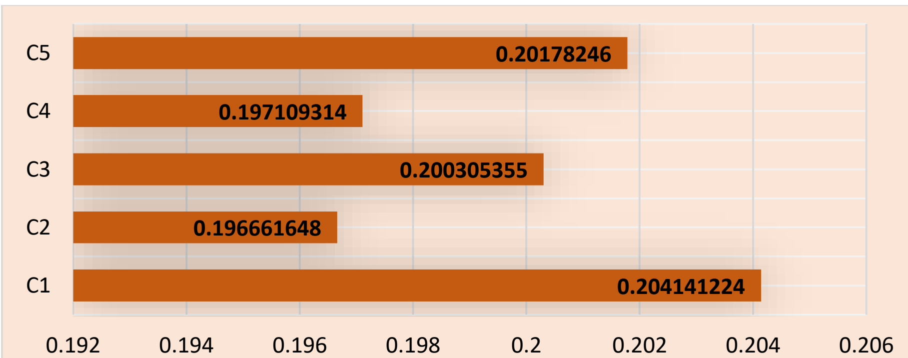

Figure 2. Weights of criteria based on Entropy-SVNSs.

Thirdly, WSM based on SVNSs is volunteering to recommend the most sustainable digital manufacturer to be the optimal one.

Step 1: We normalize the aggregated matrix in Table 2 through utilizing Eq. (7) and Table 5 is generated as normalized matrix.

Step 2: Eq. (10) plays vital role to generated weighted decision matrix through multiply entropy's weights by normalized matrix has been showcased in Table 6.

Step 3: The alternatives (An) are rating according to Eq. (11) through calculating global score for each alternative and recommend optimal one. According to Figure 3, we concluded that ME_2 otherwise ME_3.

Table 5. Normalized decision matrix based on WSM-SVNSs.

	C_1	C_2	C_3	C_4	C_5
ME_1	0.3454	0.2310	0.4028	0.2438	0.1549
ME_2	0.3775	0.2986	0.2000	0.1875	0.3216
ME_3	0.1606	0.2535	0.2000	0.2750	0.1549
ME_4	0.1165	0.2169	0.1972	0.2938	0.3685

Table 6. Weighted decision matrix based on WSM-SVNSs.

	C_1	C_2	C_3	C_4	C_5
ME_1	0.4778	0.4556	0.8056	0.4333	0.3667
ME_2	0.5222	0.5889	0.4000	0.3333	0.7611
ME_3	0.2222	0.5000	0.4000	0.4889	0.3667
ME_4	0.1611	0.4278	0.3944	0.5222	0.8722

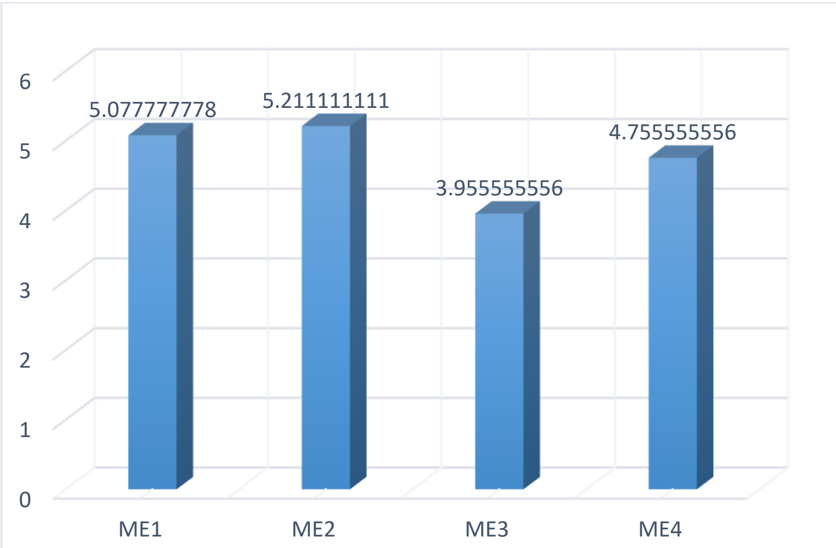

Figure 3. Ranking alternatives of manufacturers based on WSM-SVNSs.

5. Conclusions

In this study, we attempted to answer the question of why I 5.0 is important for SC especially the manufacturer as a partner in SC. Also, this study attempted to highlight the role of I 5.0 during disruptions in the business environment as the COVID-19 pandemic. Hence, the earlier studies endeavored to illustrate how I 5.0 agenda may help manufacturing be more sustainable.

Manufacturing enterprises are always under pressure to change their production methods in order to compete in the market. Using technology such as BDA in SC, especially manufacturer cases supports it to enhance decision making and support it to be proactive through analyzing real-time data and historical to predict what will happen and recognize what will be done and suitable actions.

Herein, we constructed ADM for appraising the manufacturing enterprises. The criteria in this process are vital factors in the appraisal. So, we determined the most influenced criteria which related to AI-BDA as technologies of I 5.0. In ADM MCDM techniques are supported by uncertainty theory where each technique has a vital function. For instance, Entropy is merged with SVNSs to generate a vector of criteria's weights. The results from these techniques indicated that C1 has the highest weight value of 0.204 while C2 is the lowest one with a value of 0.196.

The generated vector of weights contributes to recommending optimal and sustainable ME. In this stage, WSM under SVNSs are utilized for rating alternatives (ME n) which embrace BDA and AI techniques. The results from these techniques indicated that ME2 is optimal one and other manufacturers are ranking as ME2>ME1>ME4>ME3

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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.

Conflict 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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