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An Intuitionistic Fuzzy Multi-Criteria Approach for Prioritizing Failures That Cause Overproduction: A Case Study in Process Manufacturing

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Abstract: Overproduction is one of the most significant wastes of Lean that can occur in any manufacturing company. Identifying and prioritizing failures that lead to overproduction are crucial tasks for operational managers and engineers. Therefore, this paper presents a new approach for determining the priority of failures that cause overproduction, based on an intuitionistic fuzzy Multi-Criteria Optimization model and the Failure Mode and Effects Analysis framework. The existing vagueness in the relative importance of risk factors and their values is described using natural language words, which are modeled with trapezoidal intuitionistic fuzzy numbers. Determining the relative importance of risk factors is defined as a fuzzy group decision-making problem, and the weight vector is obtained by applying the proposed Analytical Hierarchy Process with trapezoidal intuitionistic fuzzy numbers. The compromise solution, as well as the stability check of the obtained compromise solution, is achieved using the proposed Multi-Criteria Optimization and Compromise Solution with trapezoidal intuitionistic fuzzy numbers. The proposed model was applied to data collected from a process manufacturing company.

Keywords: priority of failures; overproduction; trapezoidal intuitionistic fuzzy sets; IF-AHP; IF-VIKOR

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1. Introduction

With rising customer demands, maintaining profitability, competitiveness, and market position in the long term are the most important strategic goals of small and medium enterprises (SMEs), especially manufacturing SMEs operating in developing countries. The realization of these strategic goals and the enhancement of the manufacturing process, among other things, can be achieved by eliminating non-value-adding activities in the manufacturing process that consume resources that the customer is not willing to pay for. In new management concepts, these non-value-adding activities are referred to as waste.

One of the very important wastes in manufacturing enterprises, recognized as one of the wastes of Lean, is overproduction. In the relevant literature, some studies analyze this waste. The significance of reducing overproduction is not only reflected in its negative impact on stock creation and potential product obsolescence but also in its influence on creating other wastes. For example, overproduction due to lack of storage space can affect wastes such as motion, waiting, defects, etc. [1].

Overproduction requires the utilization of production capacities more than necessary. Therefore, machines and equipment, as well as operators and other employees, are burdened [2]. Furthermore, a significant issue with overproduction is the investment of funds in purchasing raw materials.

Based on the provided facts [1,2], it can be concluded that at the strategic level, overproduction can lead to inefficient resource allocation and increased storage costs, further burdening an enterprise's financial resources. Additionally, it can result in longer production and delivery cycles, which can negatively impact customer satisfaction and market competitiveness. By reducing overproduction, companies can improve their operational efficiency, reduce costs, and become more agile and adaptable to market changes.

Therefore, in this paper, the problem of failure analysis in the manufacturing process that causes overproduction in SMEs of process manufacturing is considered. The operational management problem addressed is complex and can be divided into two sub-problems: (1) evaluation and ranking of failures that lead to overproduction, and (2) determining adequate measures that can lead to the reduction or elimination of identified failures.

There are no strict recommendations on how to determine the failures that occur in the manufacturing process. It is common for these failures to be determined based on the opinions and assessments of decision-makers (DMs), relying on their experience and available evidence data. As discussed in this paper, the failures in the manufacturing process for SMEs are defined according to Gojković et al. [3]. The assessment of identified failures is most often based on the Failure Mode and Effects Analysis (FMEA) method. However, Liu et al. [4] suggest that conventional FMEA has some disadvantages. Many researchers propose that these disadvantages of FMEA could be eliminated or significantly reduced by combining FMEA with other methods [5]. FMEA is most often combined with Multi-Criteria Decision Making (MCDM) methods that have been extended with fuzzy sets theory [6].

Intuitionistic fuzzy sets (IFSs) [7] allow ambiguities to be quantitatively presented in a satisfactory manner. IFSs introduce additional flexibility into set descriptions (membership function, non-membership function, and intuitionistic fuzzy index) and offer a generalization of fuzzy sets [7]. Intuitionistic fuzzy numbers (IFNs) represent a special case of IFSs [8], defined on the real line. Triangular intuitionistic fuzzy numbers (TIFNs) and trapezoidal intuitionistic fuzzy numbers (TrIFNs) are two typical types of IFNs, holding significant theoretical and practical relevance [9]. In this paper, all existing uncertainties are modeled using TrIFNs, which capture ambiguity more effectively than TIFNs.

Failure prioritization can be framed as a Multi-Criteria optimization task. The relative importance of the criteria (in this case, risk factors (RFs)) is established using a pairwise comparison matrix whose elements are intuitionistic fuzzy numbers [10,11]. In this paper, the priority of failures is determined by applying the MCDM method called VIšeKriterijumska Optimizacija i Kompromisno Rešenje (VIKOR) [12], extended with TrIFNs (IF-VIKOR). By employing the VIKOR method, a compromise optimal solution is obtained, which is a key advantage of this method compared to other MCDM methods.

Respecting the type of criteria, the Fuzzy Positive Ideal Solution (IF-PIS) and Fuzzy Negative Ideal Solution (IF-NIS) are defined according to [13]. The distance between IF-PIS and IF-NIS is determined based on the application of various measures [14]. In this study, the distance between IF-PIS and IF-NIS is calculated using Euclidean distances. Additionally, it should be noted that the choice of distance measure can impact the stability of the solution. The overall VIKOR index is obtained following the conventional VIKOR method.

The following starting points can be highlighted as motivation for conducting this research: (a) continuous improvement of the reliability of the production process is essential; the manufacturing process is a crucial aspect of manufacturing SMEs, contributing significantly to gross domestic products; and (b) there are limited research papers addressing the prioritization of failures in manufacturing processes using FMEA and MCDM with IFNs.

The comprehensive objective of this research can be outlined as a combination of these approaches: (i) modeling existing uncertainties using TrIFNs, (ii) determining RFs weights as a fuzzy group decision-making problem solved by the Analytical Hierarchy Process with TrIFNs (IF-AHP), (iii) establishing the priorities of failure from the aspect of overproduction by applying the proposed VIKOR method with TrIFNs (IF-VIKOR), and (iv) arranging the implementation order of management activities based on the determined priority of failures. This approach aims to enhance the effectiveness and reliability of the manufacturing process within the shortest time and at minimal cost.

The paper comprises five main sections: In Section 2, a literature review is provided. The proposed model is explained and presented in Section 3. Following that, a case study and discussion are presented in Section 4. Finally, Section 5 presents the conclusions of this research.

2. Literature Review

Improving the effectiveness and reliability of the manufacturing process is a crucial aspect of the strategic efforts undertaken by operational management. One approach to enhancing the effectiveness and reliability of the manufacturing process involves implementing appropriate management initiatives aimed at mitigating failures. Given limited financial resources, it becomes imperative to prioritize the elimination of failures with the most significant impact on the manufacturing process. Arunagiri and Gnanavelbabu [15] proposed a model for prioritizing failures and emphasized the necessity of implementing management interventions to reduce or eliminate failures ranked within the top three positions. In practice, the sequence of management initiatives is typically determined based on the ranking of failures derived from FMEA. However, it is important to note that certain limitations of this method have been observed [4]:

- Assessing the value of the severity of the consequence (waste), the frequency of occurrence, and the likelihood of detecting failures at the level of each failure is challenging when using numerical scales of measurement;
- The weights of the RFs (criteria) are unequal;
- There is no clear, mathematically based explanation as to why the index used for ranking failures is calculated as the product of the values of the three considered criteria;
- The implications of waste in the manufacturing process, resulting from the existence of two or more failures that have the same index value, can vary significantly.

This problem can be described as a two-stage MCDM model with TrIFNs. Firstly, the proposed IF-AHP model is employed to determine the weight vector of RFs. Subsequently, the priority of considered failures in the manufacturing process is established using IF-VIKOR. This section provides a literature review in three areas: (1) applications of the MCDM method in FMEA and (2) IF-VIKOR.

2.1. Recent Applications of MCDM with Intuitionistic Fuzzy Sets in FMEA

The literature contains numerous studies wherein failure analysis and prioritization rely on the FMEA framework and various MCDM methods extended with fuzzy sets theory [6]. Table 1 showcases some applications that integrate FMEA, MCDM, and intuitionistic fuzzy sets theory.

Table 1. Approaches in the relevant literature that combine FMEA, MCDM, and intuitionistic fuzzy sets theory.

Authors	The Weights Vector of RFs	RFs Values/Aggregation Procedure	The Failures Priorities	The Domain Application
Ilangkumaran et al. [10]	IF-AHP	TIFNs	IF-AHP	Critical components priority in the paper industry
Safari et al. [16]	The fuzzy averaging operator	TIFNs	IF-VIKOR	Risk analysis in complex projects
Liu et al. [17]	Fuzzy assessments by DMs	IVIFNs	IF-TOPSIS	Electronic industry
Wang et al. [18]	IF-ANP	IVIFNs	IF-COPRAS	Hospital service
Govindan and Jepsen [19]	-	TrIFNs	IF-ELECTRE	Supplier risk assessment

Table 1. *Cont.*

Authors	The Weights Vector of RFs	RFs Values/Aggregation Procedure	The Failures Priorities	The Domain Application
Sakthivel et al. [11]	The fuzzy aggregation method/IF-AHP	TIFNs/the proposed fuzzy aggregation method	IF-TOPSIS/IF-VIKOR	Risk assessment in process manufacturing
Mirghafoori et al. [20]	Fuzzy entropy method	TIFNs/the fuzzy averaging method	IF-VIKOR	Analyses failure modes in electronic library
Tian et al. [21]	The fuzzy Best Worst Method /Fuzzy Order Weighted Averaging operator	TIFNs/IF-OWA	IF-VIKOR	Analysis failures in an automation production system
Mangeli et al. [22]	Logarithmic fuzzy preference programming	TIFNs	IF-TOPSIS	Risk analysis in production enterprises
Kushwaha et al. [23]	Intuitionistic Fuzzy Weighted Arithmetic Operator	IVIFNs	IF-TOPSIS	Sugar mill industry
Carnero [24]	Normal distribution-based method developed [25]	IVIFNs	IF-PAPRIKA	Waste Segregation
Omidvari et al. [26]	IF-BWM	IVIFNs	IVIFCODAS	Fire risk in hospitals and health centers
Yener and Can [27]	Intuitionistic Fuzzy Weighted Geometric Operator	TIFNs	IF-MABAC	Assembly line in electromechanical sector
Ilbahar et al. [28]	IF-AHP	IVIFNs	IF-AHP	Renewable energy investment risks
Nestić et al. [29]	IVIFNs	IVIFWG	IV-TOPSIS	Ranking of quality performance indicators
The proposed model	IF-AHP	TrIFNs	IF-VIKOR	Priority of failures in the process manufacturing industry

Through an analysis of the papers (see Table 1), it becomes evident that over the last decade, numerous authors have integrated various MCDM methods with intuitionistic fuzzy sets and the FMEA framework. Almost universally, these authors contend that the relative importance of RFs is unequal and propose diverse methods for calculating the weight vectors of RFs. Many of them advocate for the utilization of Interval-valued Intuitionistic Fuzzy Numbers (IVIFNs) to model the importance and value of RFs [17,18,23,24,26,28,29].

Other authors hold the belief that the importance and value of RFs can be adequately described using TIFNs [10,11,16,20–22,27]. It is widely acknowledged that the trapezoidal membership function captures uncertainty more effectively than the triangular one. Therefore, some authors have depicted the uncertainties and values of risk factors using TrIFNs [19], as also demonstrated in this research.

It is important to note that a minority of authors have determined the relative importance of RFs by framing the problem as a group decision-making issue [11,21], akin to the approach taken in this paper. In this research, it was assumed that the relative importance of each pair of RFs is separately considered at the level of each DM. Aggregated values are derived using fuzzy arithmetic mean. The fuzzy pairwise comparison matrix, which denotes the relative importance of RFs, is outlined in [10,11,18,26,28], as well as in this research. Some authors argue that collecting and processing data is more straightforward using the Best Worst Method [30] compared to setting data using pairs of relative importance ratio comparisons [21,26].

Determining the value of RFs is framed as a fuzzy group decision-making problem [11,20,21]. In the conventional FMEA method, it is assumed that the values of RFs are determined by the consensus of DMs. In other analyzed papers, including this one, the determination of RF values is based on the conventional FMEA assumption.

The ranking of failures relies on the utilization of various MCDMs that have been augmented with intuitionistic fuzzy sets. As evident in Table 1, the extension of IF-VIKOR was employed to prioritize process failures encountered by companies across different economic sectors. Comparing the proposed IF-VIKOR with the model presented in this paper reveals both similarities and differences. One significant distinction lies in their respective domains of application, which could also be considered advantageous.

2.2. Literature Related to IF-VIKOR

A comparative analysis of the proposed model and the various versions of IF-VIKOR is presented in Table 2.

Table 2. Comparative analysis of the IF-VIKOR approach in the relevant literature.

Authors	Type/Domain of Linguistic Variable	The Aggregation Procedure/Normalization Procedure	IF-PIS and IF-NIS	The Group Utility Value	The Individual Regret Value	The General VIKOR Index	Compromise Solution Stability Check
Wan et al. [31]	TIFNs/[5–10]	TFWA [32]/Normalization procedure [33]	Veto concept [13]	Hamming distance and Euclidean distance/Crisp	Conventional VIKOR	Crisp	No
Gupta et al. [34]	TrIFNs/[0–1]	TFWA [30]/Normalization procedure [33]	Veto concept [13]	Hamming distance/Crisp	Conventional VIKOR	Crisp	Yes
Mirghafoori et al. [20]	Crisp	Arithmetic mean/Normalization procedure [33]	The proposed procedure by [35]	Fuzzy algebra rules [7]	Fuzzy algebra rules [7]	Crisp by using the proposed defuzzification procedure	No
Tian et al. [21]	TIFNs	TFWA [32]/No	The proposed procedure by [35]	The proposed procedure and fuzzy algebra rules/Uncertain	The proposed procedure and fuzzy algebra rules	Crisp by using the proposed defuzzification procedure	No
The proposed model	TrIFNs/[1–9]	No/No	Veto concept [13]	Euclidean distance/Crisp	Conventional VIKOR	Crisp	Yes

A comparative analysis of the papers (refer to Table 2) and the proposed model can reveal certain differences that highlight the advantages of the proposed model. One of the main distinctions lies in the method used to determine the weight vector.

Gupta et al. [34] introduced the assumption that the values of the decision matrix elements can be modeled by TrIFNs, an approach employed in this paper. In contrast, other analyzed papers utilize TIFNs for modeling these variables. However, many authors argue that TIFNs may not effectively describe uncertainty since the peak of their membership function is concentrated at a single point (the same applies to the non-membership function). In the analyzed papers, the determination of RF values was approached as a fuzzy group decision-making problem. Aggregating DM's estimates can be achieved through various operators such as the Triangular Fuzzy Weighted Aggregation Operator (TFWA) [21] and fuzzy arithmetic mean [20]. In this paper, RF value estimation is based on achieving consensus.

Many authors argue that the criteria for evaluating the considered alternatives are not of the same type [20], necessitating the need for normalization. However, in this research, the considered RFs are of different types. It is assumed that DMs take into account the types of RFs during assessment, eliminating the need for the normalization procedure. This approach significantly reduces computational complexity. The determination of the fuzzy positive ideal solution (IF-PIS) and the fuzzy negative ideal solution (IF-NIS) is based on an analogy assumption introduced by [13], similar to the approach used in this research. Furthermore, the stability of the compromise solution, as demonstrated in [34], was verified, highlighting a key advantage of the proposed IF-VIKOR approach.

Upon examining Tables 1 and 2, it can be concluded that the problem addressed in this study has not yet been explored in the relevant literature using the proposed methodology. The authors have identified the potential of this research problem, which could serve as a guideline for future research in this field.

3. Methodology

To enhance the comprehension of the proposed methodology, this section is divided into several parts, each providing detailed explanations. Section 3.1 presents the preliminaries, Sections 3.2 and 3.3 explain the procedure for modeling uncertain values, while Section 3.4 provides the proposed algorithm.

3.1. Preliminaries

Definition 1. *An intuitionistic fuzzy set A that is in the universe of discourse X can be presented in the following way [7]:*

$$\widetilde{A} = \left(x,\ \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \middle| x \in X \right). \tag{1}$$

where:

The numbers $\mu_{\widetilde{A}}(x) \to [0,1]$ and $\vartheta_{\widetilde{A}}(x) \to [0,1]$ represent the membership degree and non-membership degree.

Where the following conditions apply:

$$0 \le \mu_{\widetilde{A}}(x) + \vartheta_{\widetilde{A}}(x) \le 1,\ \forall x \in X. \tag{2}$$

For any intuitionistic fuzzy set $\widetilde{A}$ from set X, the following applies:

$$\pi_{\widetilde{A}}(x) = 1 - \mu_{\widetilde{A}}(x) - \vartheta_{\widetilde{A}}(x). \tag{3}$$

$0 \le \pi_{\widetilde{A}}(x) \le 1, \forall x \in X.$

The value of $\pi_{\widetilde{A}}(x)$ is denoted as the degree of indeterminacy (or hesitation). The smaller $\pi_{\widetilde{A}}(x)$, denotes that the $\widetilde{A}$ is more certain.

Definition 2. *An IFS* $\widetilde{A} = \left(x,\ \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \middle| x \in X \right)$ *of the real line is defined as an intuitionistic fuzzy number (IFN) whose membership function and non-membership function are defined in [36]. The TrIFNs can be simply presented as:*

$$\widetilde{A} = \left([a_1, a_2, a_3, a_4]; \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \right). \tag{4}$$

If $a_1 \ge 0$ and one of the three values, a_2, a_3, a_4 is not equal to 0, then the TrIFN $\widetilde{A} = \left([a_1, a_2, a_3, a_4]; \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \right)$ is called a positive TrIFN.

Definition 3. *Let* $\widetilde{A} = \left([a_1, a_2, a_3, a_4]; \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \right)$ *and* $\widetilde{B} = \left([b_1, b_2, b_3, b_4]; \mu_{\widetilde{B}}(x), \vartheta_{\widetilde{B}}(x) \right)$ *be two positive TrIFNs. And* λ *is a real number. The operations of these TrIFNs are [37]:*

$$\widetilde{A} + \widetilde{B} = \left([a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4];\ min\left(\mu_{\widetilde{A}}(x), \mu_{\widetilde{B}}(x) \right), max\left(\vartheta_{\widetilde{A}}(x), \vartheta_{\widetilde{B}}(x) \right) \right), \tag{5}$$

$$\widetilde{A} - \widetilde{B} = \left([a_1 - b_4, a_2 - b_3, a_3 - b_2, a_4 - b_1];\ min\left(\mu_{\widetilde{A}}(x), \mu_{\widetilde{B}}(x) \right), max\left(\vartheta_{\widetilde{A}}(x), \vartheta_{\widetilde{B}}(x) \right) \right), \tag{6}$$

$$\widetilde{A} \cdot \widetilde{B} = \left([a_1 \cdot b_1, a_2 \cdot b_2, a_3 \cdot b_3, a_4 \cdot b_4]; min\left(\mu_{\widetilde{A}}(x), \mu_{\widetilde{B}}(x) \right), max\left(\vartheta_{\widetilde{A}}(x), \vartheta_{\widetilde{B}}(x) \right) \right), \tag{7}$$

$$\lambda \cdot \widetilde{A} = \left([\lambda \cdot a_1, \lambda \cdot a_2, \lambda \cdot a_3, \lambda \cdot a_4]; \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \right), \tag{8}$$

$$\left(\widetilde{A} \right)^{-1} = \left(\left[\frac{1}{a_4}, \frac{1}{a_3}, \frac{1}{a_2}, \frac{1}{a_1} \right]; \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \right). \tag{9}$$

Definition 4. *Let:* $\widetilde{A} = \left([a_1, a_2, a_3, a_4]; \mu_{\widetilde{A}}(x), \vartheta_{\widetilde{A}}(x) \right)$ *and* $\widetilde{B} = \left([b_1, b_2, b_3, b_4];\ \mu_{\widetilde{B}}(x), \vartheta_{\widetilde{B}}(x) \right)$ *be two positive TrIFNs. The Euclidian distance between two TrIFNs is defined [14]:*

$$d\left(\tilde{A},\tilde{B}\right) = \frac{1}{2}\cdot\sqrt{(a_1-b_1)^2+(a_2-b_2)^2+(a_3-b_3)^2+(a_4-b_4)^2+max\left\{\left(\mu_{\tilde{A}}(x)-\mu_{\tilde{B}}(x)\right)^2,\ \left(\vartheta_{\tilde{A}}(x)-\vartheta_{\tilde{B}}(x)\right)^2\right\}}. \quad (10)$$

Definition 5. *The defuzzification procedure can be defined as mapping IFs $\tilde{A}$ a real number. The defuzzification procedure is realized through the following steps [38]:*

Convert the IFs $\tilde{A}$ to (standard) fuzzy sets, and
The defuzzification procedure is used to evaluate the standard fuzzy set value.
By introducing the operator,
$D_\lambda\left(\tilde{A}\right) = \left(\left(x, \mu_{\tilde{A}}(x) + \lambda\cdot\pi_{\tilde{A}}(x), \vartheta_{\tilde{A}}(x) + (1-\lambda)\cdot\pi_{\tilde{A}}(x)\middle| x \in X\right)\right)$ [5],
and $\lambda \in [0,1]$.
Where $D_\lambda\left(\tilde{A}\right)$ presents a standard subset with the following membership function:

$$\mu_\lambda(x) = \mu_{\tilde{A}}(x) + \pi_{\tilde{A}}(x). \quad (11)$$

The crisp value of IFS $\tilde{A}$, $Val_a\left(\tilde{A}\right)$ can be given using the center of gravity method [38]:

$$Val_a\left(\tilde{A}\right) = \frac{\int_{-\infty}^{\infty} x\cdot\mu_\lambda(x)}{\int_{-\infty}^{\infty} \mu_\lambda(x)}. \quad (12)$$

3.2. Definition and Modelling of RFs' Relative Importance

Formally, RFs can be represented by a set of indices $k = \{1, \ldots, k, \ldots K\}$. The total number of RFs is denoted as K, where k, $k = 1, \ldots, K$ is the index of RF. In this research, identified failures are evaluated according to three RFs (by analogy to conventional FMEA): the severity of the consequences arising from the realization of the failure ($k = 1$), the occurrence of failure ($k = 2$), and the possibility of failure detection ($k = 3$).

The relative importance of RFs, as well as their values, are estimated by DMs (FMEA team leader, quality manager, production manager). It is introduced that DMs formally can be represented by $\{1, .., e, .., E\}$, where E is the total number of considered DMs. The index of DM is denoted as e, $e = 1, ..., E$. The number of linguistic terms depends on respecting the complexity of the problem. In this research, the modeling of predefined linguistic statements is based on TrIFNs [7]. The four-point scale and the five-point scale are used to describe the relative importance of RFs and their values, respectively.

The elements of this matrix are described by pre-defined linguistic terms and their appropriate TrIFNs are:

- equal importance (E): $([1,1,1,1]; 0.9, 0.1)$,
- low importance (L): $([1,1,2,5]; 0.8, 0.1)$,
- medium importance (M): $([1,2.5,3.5,5]; 0.6, 0.3)$, and
- high importance (H): $([1,4,5,5]; 0.7, 0.2)$.

The domains of considered TrIFNs are set into real line intervals [1–5]. A value of 1 indicates the lowest and 5 the highest relative importance of RFs. DMs do not have enough knowledge about the importance of RFs, which indicates the overlap of TrIFNs.

It can be assumed that all DMs have equal importance in the decision-making process so the aggregation of opinions of DMs into a unique rating assessment is calculated by the fuzzy averaging operator [7].

As is well known, if the pairwise comparison matrix is consistent, then the fuzzy pairwise comparison matrix is also consistent.

Therefore, in this paper, the elements of this aggregated fuzzy pairwise comparison matrix are transformed into precise numbers using the centroid moment method [38]. AHP [39] is applied for the calculation of the weights vector of RFs.

3.3. Definition and Modelling of RF's Values

Formally, failures can be presented by a set of indices $i = \{1, \ldots, i, \ldots I\}$. The total number of failures is denoted as I, and i, $i = 1, \ldots, I$ is the index of failure. Failures that cause overproduction are [3]: Imbalance of production lines ($i = 1$), Inadequate use of automation ($i = 2$), Poor assessment of market demands ($i = 3$), Poor application of just-in-case logic ($i = 4$), and Low knowledge and skills of employees ($i = 5$). In the general case, failures can be estimated for multiple RFs.

It is supposed that the RFs can be adequately described using five linguistic expressions, which are modeled by TrIFNs:

- very low value (VLV): $([1, 1, 2, 3.5]; 0.7, 0.2)$,
- low value (LV): $([1, 2, 3, 4]; 0.8, 0.1)$,
- medium value (MV): $([3, 4.5, 5.5, 7]; 0.5, 0.4)$,
- high value (HV): $([6, 7, 8, 9]; 0.6, 0.3)$, and
- very high value (VHV): $([7.5, 8, 9, 9]; 0.8, 0.1)$.

The domains of TrIFNs are presented on a usual scale (1–9). The value 1 and the value 9 indicate the smallest and largest RF values. The membership functions and non-membership functions of defined TrIFNs are defined by DMs. It should be noted that the estimations of RF values are made by consensus. DMs make decisions based on knowledge and experience as current information.

3.4. The Proposed Algorithm

For easier understanding of the proposed model, a notation has been introduced, listing the basic definitions of all indices and variables in the formulas:

E—total number of DMs;
$e, e = 1, \ldots, E$—indices of DMs;
K—total number of RFs;
$k, k = 1, \ldots, K$—indices of RFs;
I—total number of failures;
$i, i = 1, \ldots, I$—indices of failure;
$\widetilde{W}_{kk'}$—the fuzzy relative importance of k compared to k' (AHP method);
ω_k—weight vector of RF, $k, k = 1, \ldots, K$ (AHP method);
$\widetilde{x}_{ik}$—element of the fuzzy decision matrix;
$\widetilde{z}_{ik}$—element of the fuzzy weighted decision matrix;
$\widetilde{f}_k^{+}$—Fuzzy Positive Ideal Solution (VIKOR method);
$\widetilde{f}_k^{-}$—Fuzzy Negative Ideal Solution (VIKOR method);
S_i—the group utility value (VIKOR method);
R_i—the individual regret value (VIKOR method);
g_i—the General VIKOR index.

Step 1. Fuzzy rating of the relative importance of RF k over k' , k, $k' = k = 1, \ldots, K$; $k \neq k'$ is performed by each DM $e, e = 1, \ldots, E$:

$$\widetilde{W}_{kk'}^{e} = \left(\left[a_{1kk'}^{e}, a_{2kk'}^{e}, a_{3kk'}^{e}, a_{4kk'}^{e} \right]; \mu_{kk'}^{e}, \vartheta_{kk'}^{e} \right). \quad (13)$$

Step 2. The relative importance pairwise comparison matrix of RFs is given as:

$$\left[\widetilde{W}_{kk'} \right]_{KxK}; \quad (14)$$

where:

$$\widetilde{W}_{kk'} = \frac{1}{E} \cdot \sum_{e=1}^{E} \widetilde{W}_{kk'}^{e}. \tag{15}$$

and $\widetilde{W}_{kk'} = \left(\left[a_{1kk'}, a_{2kk'}, a_{3kk'}, a_{4kk'} \right]; \mu_{kk'}, \vartheta_{kk'} \right)$, which is given using fuzzy operations.

Step 3. Transformation of the fuzzy pairwise comparison matrix into the crisp pairwise comparison matrix is conducted by applying the procedure defined in [38]:

$$[W_{kk'}] \tag{16}$$

The consistency of the estimates provided by DMs is assessed using the eigenvector method. If the Consistency Index (CI) is less than or equal to 0.1, it can be concluded that the errors made by the DMs in their assessments do not significantly affect the accuracy of the solution.

Step 4. Calculating the weights of RFs is based on applying a fuzzy geometric mean:

$$\widetilde{\omega}_k = \left(\begin{array}{c} \left[\frac{\sqrt[K]{\prod_{k'} a_{1kk'}}}{\sum_{k=1,..,K} \sqrt[K]{\prod_{k'} a_{4kk'}}}, \frac{\sqrt[K]{\prod_{k'} a_{2kk'}}}{\sum_{k=1,..,K} \sqrt[K]{\prod_{k'} a_{3kk'}}}, \frac{\sqrt[K]{\prod_{k'} a_{3kk'}}}{\sum_{k=1,..,K} \sqrt[K]{\prod_{k'} a_{2kk'}}}. \frac{\sqrt[K]{\prod_{k'} a_{4kk'}}}{\sum_{k=1,..,K} \sqrt[K]{\prod_{k'} a_{1kk'}}} \right]; \\ \min_{k=1,..,K} \mu_{kk'}^{e}, \min_{k=1,..,K} \vartheta_{kk'}^{e} \end{array} \right). \tag{17}$$

$$\widetilde{\omega}_k = ([a_{1k}, a_{2k}, a_{3k}, a_{4k}]; \mu_k, \vartheta_k). \tag{18}$$

Step 5. The fuzzy decision matrix is stated as:

$$\left[\widetilde{\mathrm{x}}_{\mathrm{ik}} \right]_{\mathrm{I} \times \mathrm{K}}, \tag{19}$$

where $\widetilde{\mathrm{x}}_{\mathrm{ik}}$ is TrIFN that describes the value of RF $k, k = 1, \ldots, K$ for failure $i, i = 1, \ldots, I$, so that:

$$\widetilde{x}_{ik} = ([b_{1ik}, b_{2ik}, b_{3ik}, b_{4ik}]; \lambda_{ik}, \varphi_{ik}). \tag{20}$$

Step 6. The weighted fuzzy decision matrix is constructed as:

$$\left[\widetilde{z}_{ik} \right]_{I \times K}, \tag{21}$$

where $\widetilde{z}_{ik}$ is TrIFN that describes the value of the weighted value of RF $k, k = 1, \ldots, K$ for failure $i, i = 1, \ldots, I$, so that:

$$\begin{array}{c} \widetilde{z}_{ik} = \widetilde{\omega}_k \cdot \widetilde{x}_{ik} = ([a_{1k}, a_{2k}, a_{3k}, a_{4k}]; \mu_k, \vartheta_k) \cdot ([b_{1ik}, b_{2ik}, b_{3ik}, b_{4ik}]; \lambda_{ik}, \varphi_{ik}) = \\ \left([a_{1k} \cdot b_{1ik}, a_{2k} \cdot b_{2ik}, a_{3k} \cdot b_{3ik}, a_{4k} \cdot b_{4ik}]; \min_{k=1,..,k} (\mu_k, \lambda_{ik}), \min_{k=1,..,K} (\vartheta_k, \varphi_{ik}) \right) = \\ \widetilde{z}_{ik} = ([c_{1ik}, c_{2ik}, c_{3ik}, c_{4ik}]; \mu_{ik}, \vartheta_{ik}). \end{array} \tag{22}$$

Step 7. Let them be FPIS, $\widetilde{f}_k^{+}$, and the FNIS, $\widetilde{f}_k^{-}$ set as follows:

$$\widetilde{f}_k^{+} = \left(\left[\max_i c_{1ik}, \max_i c_{2ik}, \max_i c_{3ik}, \max_i c_{4ik}, \right]; 1, 0 \right) \tag{23}$$

$$\widetilde{f}_k^{-} = \left(\left[\min_i c_{1ik}, \min_i c_{2ik}, \min_i c_{3ik}, \min_i c_{4ik}, \right]; 0, 1 \right) \tag{24}$$

Step 8. Calculate the group utility value, S_i, $i = 1, .., I$:

$$S_i = \sum_{k=1}^{K} \frac{d\left(\tilde{f}_k^{+}, \widetilde{z}_{ik}\right)}{d\left(\tilde{f}_k^{+}, \tilde{f}_k^{-}\right)}. \quad (25)$$

Step 9. The individual regret value of each failure $i, i = 1, \ldots, I$, $\widetilde{R}_i$ is:

$$R_i = \max_{k=1,\ldots,K} \frac{d\left(\tilde{f}_k^{+}, \widetilde{z}_{ik}\right)}{d\left(\tilde{f}_k^{+}, \tilde{f}_k^{-}\right)}. \quad (26)$$

Step 10. Calculate the general VIKOR index of each failure $r_i, i = 1, \ldots, I$:

$$g_i = \alpha \cdot \frac{S_i - S^+}{S^- - S^+} + (1 - \alpha) \cdot \frac{R_i - R^+}{R^- - R^+}; \quad (27)$$

where:

$$S^+ = \underset{i=1,..,I}{min} S_i, \text{ and } S^- = \underset{i=1,..,I}{max} S_i R^+ = \underset{i=1,..,I}{min} R_i, \text{ and } R^- = \underset{i=1,..,I}{max} R_i \quad (28)$$

The distance between two TrIFNs is calculated as Euclidean distance [14].

The coefficient of the decision mechanism is denoted as α, and $\alpha \in [0, 1]$. If $\alpha = 1$ then the maximum group utility of the majority and the minimum of the individual regret for the opponent are considered. In the case of $\alpha = 0$ then consider the minimum of group utility of the majority and maximum of the individual regret for the opponent. For $\alpha = 0.5$. DMs make decisions by consensus.

Step 11. The crisp values g_i, $i = 1, \ldots, I$ are sorted in increasing order. The rank of the failures corresponds to the obtained rank.

Step 12. It is necessary to check whether the failure that is ranked first in the compromise rank list fulfills two additional conditions [12].

Condition 1 (C1)—Acceptable advantage:

Let i', and i'' be failures that are ranked first and second, respectively.

Check whether the following condition is met:

$$g_{i''} - g_{i'} \geq \frac{1}{I - 1}; \quad (29)$$

where I is the total number of identified failures in the manufacturing process.

Condition 2 (C2)—Acceptable stability in decision-making:

Check whether the failure ranked first in the compromise rank list also occupies the first place in the rank lists for ($\alpha = 1$) and ($\alpha = 0$). If this condition is met, the compromise solution can be considered stable and satisfying.

If only one of the two conditions is not met, then the failure cannot be considered more important than the other identified failures in the manufacturing process. The compromise solution should be determined based on these principles:

If C1 is not met, a compromise solution can be represented by a set of failures $(i', i'', \ldots, i^m)$, where:

$$g_{i^m} - g_{i'} < \frac{1}{I - 1} \quad (30)$$

If the considered failure i' does not fulfill C2, in this case, the set of compromise solutions consists of the failures ranked first and second in the compromise rank list.

Step 13. Elimination of failures can be achieved by applying appropriate management initiatives, with the order based on the obtained rank.

For a clearer understanding of this model, a simple pseudocode is provided:

 # Application of the IF-AHP method

Step 1: Compute fuzzy rating of the relative importance of RF.
Step 2: Create the relative importance pairwise comparison matrix of RFs.
Step 3: Transform the fuzzy pairwise comparison matrix into the crisp pairwise comparison matrix.

- Assess the consistency of estimates using the eigenvector method.
- If CI <= 0.1, continue; else, indicate an error in assessments.

Step 4: Calculate the weights of RFs using fuzzy geometric mean.

 # Application of the IF-VIKOR method

Step 5: Create the fuzzy decision matrix.
Step 6: Create the weighted fuzzy decision matrix by multiplying values from Step 5 with weights from Step 4.
Step 7: Determine the FPIS and the FNIS.
Step 8: Calculate the group utility value using the standard VIKOR procedure.
Step 9: Calculate the individual regret value using the standard VIKOR procedure.
Step 10: Calculate the general VIKOR index.
Step 11: Sort the failures based on the obtained rank.
Step 12: Check the stability of the obtained solution using the standard VIKOR procedure.
Step 13: Eliminate failures based on the obtained rank.

4. Case Study

4.1. Basic Considerations of the Research

The proposed methodology is demonstrated using real-life data obtained from a manufacturing SME situated in Bosnia and Herzegovina. While not mandatory, this company utilizes FMEA analysis to evaluate and prioritize failures occurring in the manufacturing process.

Input data were collected through surveys. The questionnaire comprised two parts. Three decision-makers participated in the survey: the FMEA team leader, the quality manager, and the production manager. In this case, the problem was more complex and considered at a higher hierarchical level compared to standard FMEA analysis. Therefore, in addition to the FMEA team leader, the quality and production managers were also involved. In certain aspects, a broader consensus of people responsible for production was required. Initially, failures that cause overproduction were taken from relevant literature [3].

Both parts, or both surveys, are of a closed type. The decision-makers were provided with questions and pre-defined linguistic expressions. For each question, it was sufficient for them to select one of the linguistic expressions. In their roles, all three decision-makers are experienced, with more than 10 years of work experience, both in this and other manufacturing companies. This was one of the reasons they were chosen to participate in the research.

In the first part, DMs were provided with linguistic expressions to assess the relative importance of each pair of RFs. Each DM independently conducted the assessment. DMs expressed their decisions individually, while their assessments were aggregated using the fuzzy geometric mean operator. In this way, their individual assessments were integrated into one common value of the weight vectors.

In the second part of the survey, DMs were presented with linguistic statements to evaluate the significance of failures identified in the overproduction of waste of Lean. Consensus-based estimates for the identified failures were derived (analogous to conventional FMEA). In this case, DMs made their assessments collectively by harmonizing their opinions. This approach aligns with conventional FMEA analysis and the way FMEA teams operate in practice.

The surveys were distributed to DMs via email, and responses were collected through the same medium. The survey was conducted during the last quarter of 2023.

In both of these cases, a special guideline with pre-defined linguistic expressions modeled using TrIFNs was prepared for decision-makers. Unlike classical fuzzy numbers (type-1) or type-2 fuzzy numbers, TrIFNs and intuitionistic fuzzy numbers, in general, have an additional dimension. In addition to the membership degree, they also have a non-membership degree. This additional dimension allows for more precise and detailed modeling of uncertainty and vagueness. This enables decision-makers to better understand and quantify risks, leading to the optimization of the decision-making process and improving efficiency in risk management in industrial applications.

Many authors believe, and research shows, that the use of intuitionistic fuzzy numbers is easier to understand and use by DMs [40]. In this study, the authors, in consultation with DMs, decided to use TrIFNs because DMs expressed that this method of expressing assessments is clear to them and allows them to base their estimates on a multidimensional approach, which includes both membership degree and non-membership degree.

Empirical proof of which numbers are superior presents a challenge. In many cases, the choice between different types of fuzzy numbers, such as classical fuzzy numbers, type-2 fuzzy numbers, or intuitionistic fuzzy numbers, depends on the context of the specific problem, analysis requirements, and subjective assessments of decision-makers. Each type of number has its advantages and limitations, and the optimal choice depends on the nature of the problem being studied [41]. Therefore, it is important to consider various factors when making a selection, including the complexity of the problem, available data, and the needs of decision-makers.

4.2. Illustration of the Proposed Model

The developed methodology is illustrated on the considered SME.

The relative importance of RFs is estimated by each DM (Step 1 of the proposed Algorithm) it is presented:

$$\begin{bmatrix} E,E,E & L,M,M & L,H,H \\ & E,E,E & E,L,L \\ & & E,E,E \end{bmatrix}$$

The aggregated fuzzy pairwise comparison matrix is given:

$$\begin{bmatrix} ([1,1,1,1];0.9,0.1) & ([1,2,3,5];0.6,0.3) & ([1,3,4,5];0.6,0.3) \\ & ([1,1,1,1];0.9,0.1) & ([1,1,1.67,3.67];0.6,0.1) \\ & & ([1,1,1,1];0.9,0.1) \end{bmatrix}$$

The procedure (Step 3 of the proposed Algorithm) is:

$$\begin{bmatrix} 1 & 2.67 & 3.33 \\ & 1 & 1.67 \\ & & 1 \end{bmatrix}, C.I. = 0.01$$

By using the proposed IF-AHP (Step 4), the weights vector is obtained:

The weight of RF (k = 1):

$$\tilde{\omega}_1 = ([0.18,\ 0.45,\ 0.79,\ 1.49]; 0.6,\ 0.3)$$

$$\tilde{\omega}_2 = ([0.11,\ 0.17,\ 0.31,\ 0.79]; 0.6,\ 0.3)$$

$$\tilde{\omega}_3 = ([0.07,\ 0.13,\ 0.23,\ 0.51]; 0.6,\ 0.3)$$

The fuzzy decision matrix is stated (Step 5 to the proposed Algorithm) and presented in Table 3.

Table 3. The fuzzy decision matrix.

	k=1	k=2	k=3
i=1	MV	LV	LV
i=2	VLV	LV	LV
i=3	HV	VHV	MV
i=4	MV	LV	MV
i=5	VLV	LV	VLV

By applying the proposed procedure, the weighted fuzzy decision matrix, IF-PIS, and IF-NIS are presented in Table 4 (Step 6 and Step 7 of the proposed Algorithm).

Table 4. The aggregated fuzzy decision matrix.

	k=1	k=2	k=3
i=1	$([0.54, 2.02, 4.34, 10.43]; 0.5, 0.4)$	$([0.11, 0.34, 0.93, 3.16]; 0.6, 0.3)$	$([0.07, 0.26, 0.69, 2.04]; 0.6, 0.3)$
i=2	$([0.18, 0.45, 1.58, 5.21]; 0.6, 0.3)$	$([0.11, 0.34, 0.93, 3.16]; 0.6, 0.3)$	$([0.07, 0.26, 0.69, 2.04]; 0.6, 0.3)$
i=3	$([1.08, 3.15, 6.32, 13.41]; 0.6, 0.3)$	$([0.82, 1.36, 2.79, 7.11]; 0.6, 0.3)$	$([0.21, 0.58, 1.26, 3.57]; 0.5, 0.4)$
i=4	$([0.54, 2.02, 4.34, 10.43]; 0.5, 0.4)$	$([0.11, 0.34, 0.93, 3.16]; 0.6, 0.3)$	$([0.21, 0.58, 1.26, 3.57]; 0.5, 0.4)$
i=5	$([0.18, 0.45, 1.58, 5.21]; 0.6, 0.3)$	$([0.11, 0.34, 0.93, 3.16]; 0.6, 0.3)$	$([0.07, 0.13, 0.46, 1.78]; 0.6, 0.3)$
FPIS	$([1.08, 3.15, 6.32, 13.41]; 1, 0)$	$([0.82, 1.36, 2.79, 7.11]; 1, 0)$	$([0.21, 0.58, 1.26, 3.57]; 1, 0)$
FNIS	$([0.18, 0.45, 1.58, 5.21]; 0, 1)$	$([0.11, 0.34, 0.93, 3.16]; 0, 1)$	$([0.07, 0.13, 0.46, 1.78]; 0, 1)$

The results obtained using the proposed IF-VIKOR (from Step 8 to Step 10 of the proposed Algorithm) are presented in Table 5. Furthermore, the calculation of Euclidean distance is illustrated:

$$d\left(\tilde{f}_1^{+}, \tilde{x}_{11}\right) = \frac{1}{2}\cdot\sqrt{(0.54-1.08)^2+(2.02-3.15)^2+(3.34-6.32)^2+(10.43-13.41)^2+max\left\{(0.5-1)^2,\ (0.4-0)^2\right\}} \tag{31}$$
$$\left(\tilde{f}_1^{+}, \tilde{x}_{11}\right) = 2.2124$$

Table 5. Priority of failures.

	The General VIKOR Index for α=0.5	Compromise Rank List	The General VIKOR Index for α=0	Rank	The General VIKOR Index for α=1	Rank
i=1	0.185	2	0	1	0.369	2
i=2	1	5	1	4–5	1	5
i=3	0.007	1	0.015	2–3	0	1
i=4	0.904	4	1	4–5	0.805	4
i=5	0.314	3	0.015	2–3	0.613	3

The failure ranked first on the compromise list ($i = 3$) is not ranked first when $\alpha = 0$ and $\alpha = 1$ Let us now establish a compromise solution by applying the defined principles.

Check that the first condition is satisfied:

$$0.185 - 0.007 \geq \frac{1}{5-1} \tag{32}$$

As condition C1 is not met, the failure ($i = 3$) is not the most significant.

Check that the second condition is satisfied:

$$0.314 - 0.007 < \frac{1}{5-1} \tag{33}$$

Condition C2 is not met either.

As neither condition is met, the compromise solution involves failures: Poor assessment of market demands ($i = 3$) and Imbalance of production lines ($i = 1$). These failures have the most significant impact on the occurrence of overproduction in the considered company.

5. Discussion

The management of the considered enterprise should implement measures aimed at reducing the risk of overproduction resulting from the occurrence of this failure.

Various factors such as market structure, competition, price elasticity, product distribution routes, and changes in demand can contribute to the Poor assessment of market demands ($i = 3$). Therefore, conducting a comprehensive market analysis considering all relevant factors is crucial, as inadequate and inaccurate analysis can lead to this failure. Applying quality methods such as trend extrapolation, the Delphi method, or the Consumption level method can help reduce or eliminate the causes leading to Poor assessment of market demands ($i = 3$).

The causes of Imbalance of production lines ($i = 1$) may include poorly defined clock time, undefined process capacity, unclear determination of working elements, and imprecise hiring time for workers. Implementing the Kaizen strategy can help eliminate these causes and thereby prevent the occurrence of the Imbalance of production lines ($i = 1$) failure.

Based on the presented results, key contributions of the study can be identified from the perspective of applying the proposed MCDM approach integrated with the FMEA framework for determining the priorities of considered failures. Some of the most significant contributions are:

(1) The integration of the proposed MCDM approach and the FMEA framework for determining the priorities of the considered failures has been carried out.
(2) DMs use linguistic terms to express their assessments. In standard FMEA analysis, a scale of measures from 1 to 10 is used. It is very challenging to express qualitative indicators and evaluations using precise numbers. Therefore, the MADM approach has been expanded with TrIFNs.
(3) In basic FMEA analysis, RFs have equal importance. Many authors and practitioners disagree with this fact [4,6,17]. In this case, based on the knowledge and experience of experts (DMs) who practice the application of FMEA analysis, we have determined the importance of these RFs.
(4) The applied IF-VIKOR method is suitable for determining a compromise ranking. Based on the rules defined in the standard VIKOR method, it is possible to determine which alternatives (in this case, failures) should be selected. Thus, in addition to ranking, this method provides an optimal set of alternatives. This is crucial for the FMEA team. Standard FMEA analysis determines the priority of considered failures but does not provide a mathematical approach for choosing the sequence in which appropriate actions will be taken. In this case, we certainly know that ($i = 3$) and ($i = 1$) have the greatest impact on the occurrence of overproduction.
(5) The proposed MCDM approach is traceable, comprehensive, and most importantly, clear for DMs in practice.

Based on the presented results, the integration of the proposed MCDM approach with the FMEA framework has demonstrated significant advancements in determining the priorities of considered failures. This integration offers a more flexible and nuanced method compared to traditional approaches, allowing for the consideration of qualitative assessments through linguistic terms and addressing the varying importance of RFs. Additionally, the application of the IF-VIKOR method has enhanced the decision-making process by providing a compromise ranking and an optimal set of alternatives for action. These contributions underscore the value of the proposed MCDM approach as a comprehensive, traceable, and clear methodology, tailored to meet the practical needs of DMs in managing manufacturing process failures effectively.

6. Conclusions

In both industrial management practice and research within operational management, the ranking of failures and the definition of appropriate management initiatives are recognized as critical management challenges. In this study, failures related to the overproduction waste of Lean significantly affect the effectiveness and reliability of the manufacturing process under consideration.

The proposed model has been rigorously tested and applied to real-life data. With the increasing imperative to reduce costs, DMs must identify failures that exert the most substantial impact on the realization and costs of the manufacturing process. This aspect can be underscored as one of the practical contributions of the proposed model.

The main contributions of the conducted research are as follows:

(1) The FMEA framework is used to define RFs according to which manufacturing process failures in SMEs are assessed;
(2) DMs use linguistic terms to describe existing uncertainties, which are modeled by TrIFNs;
(3) The aggregation of the RFs' relative importance is conducted using the fuzzy averaging operator;
(4) The proposed IF-AHP has been applied to determine the weights of RFs;
(5) The priorities of failures are determined using the proposed IF-VIKOR.

The primary limitation of the proposed model is the subjectivity involved in identifying failures. Other important limitations relate to the complexity of applying the developed model:

(1) Implementing the proposed model in practice requires knowledge of relatively complex mathematical approaches and methods;
(2) Training of FMEA team members is required for the use of the model;
(3) The time for applying the FMEA methodology increases;
(4) Applying the methodology in other companies (case studies) requires additional modifications and changes.

Future research directions could include prioritizing failures at the level of waste of Lean and developing user-friendly software solutions based on the presented model, which would significantly impact the elimination of identified key limitations of this approach.

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