International Journal of Business and Management; Vol. 18, No. 6; 2023
ISSN 1833-3850 E-ISSN 1833-8119
Published by Canadian Center of Science and Education

From Uncertainty to Precision: Advancing Industrial Rework Rate Analysis with Fuzzy Logic

Fábio de Oliveira Neves[1] & Eduardo Gomes Salgado[2]

[1] Exact Science Institute, Environmental Science Department, Federal University of Alfenas, Alfenas, Brazil

[2]Exact Science Institute, Federal University of Alfenas, Alfenas, Minas Gerais State, Brazil

Correspondence: Fábio de Oliveira Neves, Exact Science Institute, Environmental Science Department, Federal University of Alfenas, Alfenas, Minas Gerais State, Brazil. E-mail: fabiooneves@gmail.com.br

Received: August 10, 2023 Accepted: October 1, 2023 Online Published: November 8, 2023

doi:10.5539/ijbm.v18n6p119 URL: https://doi.org/10.5539/ijbm.v18n6p119

Abstract

The industrial sector plays a crucial role in the global economy by providing products to meet the ever-evolving societal needs. However, the relentless pursuit of quality and efficiency faces challenges, with one of the most significant obstacles being rework. Accordingly, this paper presents the development of a rework rate index in the industrial sector, using Mamdani-type fuzzy logic as the methodology, aiming to overcome the limitations of traditional approaches and capture the complexity and uncertainty of rework data. Seventeen indicators grouped into different categories were analyzed by assessing correlations to obtain the proposed index. The results demonstrated the effectiveness of the Mamdani fuzzy logic approach in evaluating rework rates, offering comprehensive insights and clear categorizations. The analysis of correlations among indicators revealed intricate interdependencies influencing rework rates. The creation of the Rework Reduction Index signifies a significant advancement in quality and efficiency management within the industrial sector. The fuzzy approach provides a comprehensive means to address data uncertainty and subjectivity, enabling a precise and contextual evaluation of rework rates. The results have direct implications for informed decision-making, allowing companies to identify problematic areas, allocate resources efficiently, and monitor progress over time. Furthermore, the proposed approach has the potential to inspire similar practices in other companies, contributing to enhancing efficiency and quality in industrial processes Future studies could extend the application of the Rework Reduction Index to various industrial sectors and explore the relationship between index classifications and traditional performance metrics.

Keywords: rework, rework rate index, fuzzy logic, industrial efficiency, process quality

1. Introduction and Framework of the Proposal

The industrial sector plays a crucial role in the global economy, providing products that meet the needs and demands of an ever-evolving society (Shafiq et al., 2015). However, the relentless pursuit of quality and efficiency is not without challenges, and one of the most significant obstacles faced by organizations is rework (Abu et al., 2019). Rework, defined as the repetition of activities in a production process due to defects or inadequacies, results in time, resource, and cost losses (Mousavi et al., 2015). Therefore, the ability to effectively manage rework is vital to ensure the competitiveness and sustainability of industrial companies (Elkington, 1999).

In this scenario, rework emerges as a challenge of considerable impact. It is characterized by the need to redo tasks or stages of the production process due to defects, errors, or identified inadequacies (Tyagi et al., 2015). This repetition of activities not only results in the waste of material and financial resources but also compromises operational efficiency and the quality of end products (Hasan & Trianni, 2020). The search for solutions that allow for the identification, analysis, and reduction of rework has become a priority for industrial organizations seeking to maintain their competitiveness in a globalized and dynamic market (Trianni et al., 2016).

Analyzing the rework rate is a complex task, as the data associated with this phenomenon is not only quantitative but also qualitative and subjective (Musteen, 2016). Traditional metrics often fail to capture the entirety of aspects involved in rework, including nuances, variations, and the relationship between different indicators (Lee & Wakefield-Rann, 2021). Quantitative data can provide a partial view of rework but fail to fully reflect the ever-changing reality of the industry. Moreover, subjective aspects, such as the individual interpretation of rework indicators by experts, add an additional layer of complexity (Alkan & Harrison, 2019).

In this context, fuzzy logic has emerged as an effective approach to deal with the uncertainty and subjectivity inherent in rework data. Fuzzy logic allows for the representation and manipulation of information that does not fit into absolute categories but rather into intermediate degrees of relevance (Zimmermann, 2001). This is particularly relevant for assessing the rework rate, as classifications are not binary but rather a continuous scale that reflects the complex nature of rework-related issues.

The application of fuzzy logic in industrial problems has garnered considerable attention in academic literature and management practices. In previous studies, this approach has demonstrated its potential in solving complex problems in various areas. Works focused on optimizing production processes have used fuzzy logic to model uncertainties and variations in data, leading to more robust and efficient decisions (Gholizadeh et al., 2020). Furthermore, fuzzy logic has been successfully applied to decision-making problems where ambiguity and subjectivity are present, such as the evaluation of performance in complex systems (Banaeian et al., 2018). In the specific realm of quality management and rework, fuzzy logic has also been explored in a promising manner. Studies have used this approach to assess the quality of products and processes, taking into account multiple factors and indicators (Govindan et al., 2016). The flexibility of fuzzy logic allows models to closely approximate reality, considering nuances not captured by traditional methods (Suryawanshi & Dutta, 2022). Moreover, the application of fuzzy logic has proven relevant in analyzing uncertainties in production systems, enabling better adaptation to the inherent variations of industrial processes (Wang et al., 2018).

An exemplary application of fuzzy logic in problems related to quality and rework can be found in studies exploring risk assessment and decision-making in complex industrial environments (Li et al., 2022). Fuzzy logic has been used to model uncertainties and combine different sources of information, allowing for a more holistic analysis of risks and the identification of mitigating strategies (Jiang et al., 2017). Furthermore, the fuzzy approach has been applied in supplier selection and supplier performance evaluation, considering multifaceted criteria and subjective assessments (Büyüközkan et al., 2017).

Specifically, a study addressing rework rates in the industrial sector using Mamdani-type fuzzy logic carries several relevant implications for quality management, efficiency, and decision-making in the industrial context.

a) Improved Efficiency and Quality of Industrial Processes - The application would provide a robust tool to assess and manage rework rates in industrial processes. By adopting fuzzy logic, which adeptly handles uncertainties and data inaccuracies, companies can gain a more accurate understanding of the factors contributing to rework. This enables more effective identification of problematic areas, allowing for targeted corrective measures. As a result, process efficiency can be enhanced, as underlying rework causes are addressed more assertively, leading to higher-quality end products and lower operational costs (Baba et al., 2020).

b) Informed and Strategic Decision-Making - Considering process complexity and associated uncertainties, managers can rely on a more comprehensive and accurate metric to assess rework performance. This enables efficient resource allocation, priority identification, and continuous monitoring of improvements over time. Informed decision-making is crucial to strategically steer company efforts, resulting in more effective rework management aligned with organizational goals (Zhang & Mahadevan, 2017).

c) Contribution to Advancing Research and Industrial Practices - The amalgamation of fuzzy logic with rework rate assessment aligns with current trends of applying advanced methods to solve intricate challenges. The proposed approach and insights gained can serve as a reference for future studies and initiatives in the field of rework management. Additionally, the successful implementation of the index may inspire other companies to adopt similar approaches, contributing to an overall enhancement of efficiency and quality in industrial processes (Willems & Vanhoucke, 2015).

In this context, the present study aims to develop a rework rate index in the industrial sector, employing Mamdani-type fuzzy logic. The proposed approach aims to overcome the limitations of traditional approaches that rely on absolute and binary metrics, inadequately capturing the complexity and uncertainty present in rework data. Mamdani fuzzy logic offers a robust framework for modeling uncertainty and subjectivity, allowing for a more accurate and contextualized assessment of the rework rate.

The advancement of this Rework Rate Index model represents a significant step in applying innovative approaches to address the complex challenges of the industrial sector. Integrating Mamdani-type fuzzy logic into rework rate assessment offers a comprehensive and precise solution to deal with the inherent uncertainty and subjectivity in industrial data. Progressing in this direction, this model provides a valuable alternative to traditional approaches, enabling a deeper understanding of interdependencies among indicators and the multifaceted influence of factors on the rework rate (Kravchenko et al., 2019). This advancement not only contributes to the enhancement of quality and efficiency management but also inspires the continuous development of more refined strategies for optimizing industrial processes.

In the methodology section, we will detail the fundamental steps for developing the Rework Rate Index using fuzzy logic. We will begin with defining relevant indicators that encompass different aspects of the production and rework process. These indicators will be grouped into categories reflecting critical dimensions of rework in the industrial environment. Building on this strong foundation, we will move into the fuzzy modeling phase, where Fuzzy Set Theory will be employed to address the uncertainty and subjectivity inherent in rework data, with representation occurring through Pearson correlation.

At the end of the study, the relevance and implications of the results obtained with the Rework Rate Index will be discussed. The insights provided by the index have the potential to guide informed decisions and rework management strategies in the industrial sector. Furthermore, the work will contribute to the field of quality and efficiency management, offering an innovative approach to comprehensively evaluate and address rework.

In summary, the development of the Rework Rate Index using Mamdani-type fuzzy logic represents a promising approach to deal with the complexity and uncertainty of rework data in the industrial sector. By combining the precision of fuzzy logic with the contextual understanding of rework indicators, this index has the potential to significantly enhance quality and efficiency management in industrial operations.

In addition to this introduction, the paper will cover a literature review on the topic in Section 2. Section 3 will outline the methodological steps. Section 4 will present the results and discussions of the models. The implications and limitations will be addressed in the fifth section, followed by the conclusions of the present study in the sixth section.

2. Rework Rate and Fuzzy Logic

The literature review on industrial rework rates and fuzzy logic unveils the increasing significance of innovative approaches in assessing and enhancing efficiency in production processes (Schumacher et al., 2016). The rework rate, a critical indicator in industrial sectors, reflects the effectiveness of production processes, the quality of end products, and resources wasted due to errors and defects (Zeng et al., 2015). In recent years, the industry has been compelled to face an ever-evolving landscape, where the pursuit of operational excellence is paramount to maintaining competitiveness and meeting the demands of the globalized market. In this context, the rework rate emerges as a pivotal indicator, representing not only the efficiency of production processes but also the quality of end products delivered to customers (Ikumapayi et al., 2019). Rework, characterized by the effort required to rectify defects or errors in already manufactured products, directly impacts operational costs, production time, and consequently, customer satisfaction (Psarommatis & Kiritsis, 2022). The challenges associated with the rework rate are multidimensional and intricate. Modern industrial processes, often highly complex and automated, can be influenced by a variety of factors, including variations in raw materials, equipment failures, inconsistencies in assembly steps, and even human errors (Farahani et al., 2022). Traditionally, the evaluation of the rework rate has been based on quantitative metrics and analysis approaches, which may not always fully capture the multifaceted and often subjective nature of the factors contributing to rework (Y. C. Shen et al., 2016). In this context, achieving accurate and holistic assessment of the rework rate becomes an essential quest to optimize industrial processes and achieve superior outcomes (Rissman et al., 2020). However, the multifaceted and often subjective nature of factors contributing to rework makes analysis a complex task. Quantitative approaches have traditionally been used to measure and manage the rework rate (Malek & Desai, 2020). However, these approaches may not always capture the richness of nuances and interactions present in modern industrial processes.

Fuzzy logic models have gained prominence as a valuable tool to address the complexity and uncertainty associated with industrial rework rate analysis. Introduced by Lotfi Zadeh in the 1960s, fuzzy logic recognizes and embraces the ambiguous and uncertain nature of real-world information. It offers a flexible framework to deal with the imprecision and subjectivity inherent in data, enabling the representation of values not just as "true" or "false," but on a continuous scale of relevance (Abe, 2000). In recent years, the application of fuzzy logic models in rework rate analysis has garnered the attention of researchers and industry professionals, resulting in a growing body of literature. A study conducted by (dos Santos et al., 2017) employed fuzzy logic to evaluate the relationship between assembly process quality and rework rate in an electronic component production line. Similarly, (Abdel-Tawab & Noor, 1999) explored the application of a fuzzy model to analyze the influence of temperature variations on rework rate in welding processes (Hanif et al., 2023). Furthermore, the integration of fuzzy models with correlation analysis has enabled deeper insights into causal relationships and underlying patterns in the rework rate. In a 2023 study, (Karmaker et al., 2023) examined the relationship between factors such as raw material quality, automation level, and team training, using a fuzzy model to assess the impact of these factors on the rework rate. Similar findings were observed by Jones et al. (2020), who applied fuzzy logic to analyze the effects of seasonal variation on the rework rate in an electronic product production line (Battesini et al., 2021).

Furthermore, the integration of fuzzy models with correlation analysis techniques has enabled deeper insights into causal relationships and underlying patterns in the rework rate. This not only provides valuable information for managerial decision-making but also contributes to a comprehensive understanding of industrial production systems.

However, it is important to highlight that the application of fuzzy logic in industrial rework rate analysis is not without challenges. The proper definition of membership functions, the careful selection of relevant indicators, and empirical validation are critical aspects for the success of these models. Additionally, comparing fuzzy approaches with traditional methods of performance evaluation can provide insights into the effectiveness and competitive advantage of applying fuzzy logic (N. Shen et al., 2019). Despite significant advancements, challenges persist in the practical application of these models. The precise definition of rules and membership functions requires specialized knowledge, and empirical validation in real industrial environments is essential to ensure the reliability and usefulness of these models (Karatop et al., 2015).

2.1 Difficulties

One of the primary obstacles lies within the intricate nature of contemporary industrial processes. Present-day production chains frequently encompass numerous stages, diverse departments, and interactions among various components (Kozarević & Puška, 2018). This complexity renders pinpointing the root causes of rework a formidable task, as defects can originate at any juncture in the process and disseminate throughout subsequent phases. Moreover, the absence of seamless integration between data recording systems can impede effective rework tracking, making it arduous to discern recurring patterns and trends (Akhigbe et al., 2021).

Fluctuations in raw materials, environmental conditions, and operator attributes can introduce variations in end products, posing substantial challenges. These variations can result in defects that are arduous to forecast and control, escalating the complexity of analyzing rework rates (Perera & Kamalaruban, 2021). Additionally, the subjective nature of the "rework" definition can lead to disparate interpretations among team members, impacting the consistency of collated data and drawn conclusions (Franco et al., 2016).

Assessing the costs tied to rework becomes a monumental challenge. Rework encompasses not only the direct cost of rectifying a flawed product but also indirect costs, such as production delays, additional resource consumption, and ramifications on the company's reputation (Seth & Rastogi, 2019). Precisely quantifying these costs is a multifaceted task, often entailing qualitative considerations that are intricate to measure.

Analyzing rework rates can be impeded by an absence of consistent and standardized metrics. Different companies may adopt varied rework definitions, rendering comparisons between organizations and sectors intricate (Rizos et al., 2016). This can also complicate the identification of best practices and opportunities for knowledge transfer among companies.

2.2 Benefits

Faced with the inherent challenges in analyzing rework rates, the utilization of innovative approaches and advanced tools becomes imperative to overcome obstacles and gain valuable insights. In this context, fuzzy logic models emerge as a promising solution to deal with the complexity, variability, and subjectivity present in this challenging field. While conventional approaches often grapple with data uncertainty and the difficulty of handling intricate nuances, fuzzy logic offers a flexible and adaptive way to model and analyze complex systems (Sugeno, 1985). Unlike binary metrics, fuzzy logic allows for capturing degrees of relevance and uncertainty, reflecting the multifaceted nature of industrial processes (Zadeh, 1978).

The benefits of applying fuzzy logic models in rework rate analysis are diverse and impactful. Firstly, fuzzy logic enables the representation and manipulation of vague and imprecise concepts, such as "good" and "bad," "high" and "low." This enables a more realistic analysis of industrial processes, as data often do not fit neatly into rigid categories (Ragab et al., 2019). The ability to model nuances and gradations is particularly relevant in rework rate analysis, where the severity of defects can vary widely (Cortés et al., 2021).

Another significant advantage is fuzzy logic's capability to handle the subjectivity present in rework definitions. As mentioned earlier, different team members may have distinct interpretations of what constitutes rework, leading to data inconsistencies. Fuzzy logic allows for the inclusion of degrees of relevance and consideration of different perspectives, leading to more comprehensive and coherent analyses (Chanamool & Naenna, 2016).

In summary, applying fuzzy logic in rework rate analysis offers a more flexible, precise, and adaptive approach compared to traditional methods. By capturing the inherent complexity, uncertainty, and subjectivity in industrial processes, fuzzy logic enables the acquisition of richer and more relevant insights for quality and efficiency management in the industrial sector. In the next section, examples of academic works that employed fuzzy logic to address similar issues will be detailed, highlighting the relevance and effectiveness of this approach in analyzing complex and multifaceted systems.

3. Methodological Proposal

In this section, we will detail the proposed methodology for developing a Rework Rate Index in the context of the industrial sector. The use of Mamdani-type fuzzy logic will be presented as the main approach to address the complexity and uncertainty associated with rework data. Fuzzy logic is particularly suitable for dealing with vague and uncertain concepts, allowing for a more precise modeling of the variables involved.

3.1 Definition of Indicators

In the first step, indicators were identified through literature review and the industrial assessment center report to ascertain the key variables responsible for composing the industrial rework index. For this purpose, Table 1 and Figure 2 present the indicators and the architecture that comprise the current index.

Table 1. Indicators used in the fuzzy model

Group	*Indicators*	*Acronym*
Defect and Scrap Rate (1)	Rework Rate per Defect	RRD
	Scrap Rate per Batch	SRB
	Scrap Rate per Stage	SRS
	Rejection Rate per Supplier	RRS
	Rework Rate per Defect Category	RRC
Related Costs (2)	Rework Cost per Customer	RCC
	Reinspection Cost	RPC
	Rework and Scrap Cost	RSC
Process Efficiency (3)	Inspection Process Efficiency	IPE
	Defect Identification Time	DIT
	Effectiveness of Corrective Actions	ECA
Time and Productivity (4)	Average Rework Time	ART
	Average Time between Defect and Rework	ATD
Defect Origins (5)	Internal/External Rework Proportion	I/ERP
	Rework Rate per Shift	RRS
	Scrap Index per Process	SIP
Analysis and Classification (6)	Primary Cause of Rework	PCR

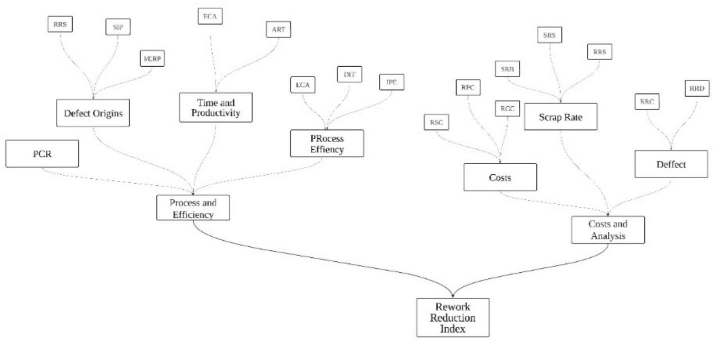

Figure 1. Architecture of the Rework Rate Index

It can be observed that this index is composed of three levels. The aggregation result of level 1 serves as input for the aggregations of level 2, which, through these results, will yield the present index.

3.2 Correlation Analysis and Interaction among Rework Indicators

The incorporation of Pearson correlation in the Rework Rate Index development process was a crucial step of statistical analysis to assess the relationships among various indicators associated with rework rates. Using a significance level of α = 95%, the Pearson correlation coefficient was applied to determine the strength and direction of linear associations among the indicators. In this stage, the purpose is to understand how different variables behave and self-correlate in the context of rework rates. By examining the relationship between the indicators, it was possible to identify consistent and statistically significant patterns that, to some extent, contributed to a deeper understanding of the interdependencies among the factors influencing rework rates.

3.3 Fuzzy Modeling with Mamdani Inference Structure

Following the indicator selection phase, we proceed to the fuzzy modeling step. Fuzzy Set Theory is an approach that deals with sets possessing imprecise boundaries, using degrees of membership rather than binary logic. This approach is particularly relevant for the data in Table 1, which exhibit distinct nuances (Zadeh, 1978).

A fundamental characteristic of fuzzy sets is the ability to define degrees of relevance. Each point in the output space is associated with a fuzzy set A, expressed by Equation 1.

$$\mu A(x) = f(x) \quad (1)$$

where f(x) is a function that assigns the degree of membership of element *x* to fuzzy set *A*.

The set operations used in this study are based on intersections, aligned with the logical operator *AND*, to reflect the experts' semantics and the nature of the membership functions of the indicators.

Constructing the fuzzy model involved defining linguistic variables by experts. For modeling membership functions, trapezoidal functions were chosen at the extremes, and triangular functions in the center. This choice allowed for a flexible approach encompassing a variety of relevant fuzzy functions (Zimmermann, 2001).

Formulating the rule bases adopted the IF <*antecedent*> THEN <*consequent*> format, where the antecedent represents the conditions of input variables that activate consequent rules through fuzzy inference.

In the application of the Mamdani structure, the aggregation step determined the fulfillment level of rule parts (IF) using the *MIN* operator intersection. The conclusion step allowed for evaluating the degree of participation, determining the degree of service (DOS) for each rule. Finally, the composition step employed the *MAX* operator union to validate conditions and determine the validity of the conclusion.

The mathematical output was obtained through defuzzification, using the centroid method, which represents a weighted midpoint. The corresponding equation is as follows, in Equation 2.

$$Centroid= \left(\frac{\sum(x(\mu))}{\sum \mu(x)}\right) \quad (2)$$

where x is the value of the output variable, and $\mu(x)$ is the corresponding membership function.

This approach provided a robust fuzzy model that considers the inherent uncertainty and imprecision of industrial sector data, enabling a precise assessment of the rework rate.

4. Results and Discussions

In this section, we present the outcomes of applying the proposed index for reducing rework rates in the industrial sector, utilizing the fuzzy logic approach. The investigated indicators provided an assessment framework aimed at offering comprehensive insights into process performance and the effectiveness of enhancement strategies (Table 1 and Figure 1).

4.1 Correlations and Associations

An in-depth analysis of correlations and associations among various indicator groups revealed valuable insights into the intricate interrelations shaping rework rates in the industrial sector. The Pearson correlation coefficient was employed to quantify linear relationships between indicators, highlighting pivotal observations that unfold as follows.

4.1.1 Correlations Among Indicator Groups

Upon applying the Pearson correlation coefficient, a statistically significant positive correlation ($r = 0.75$, $p < 0.05$) was identified between the Rework Rate per Defect indicator from Group 1: Defect and Rework Rates. In addition, the Rework and Rework Cost indicator from Group 2: Associated Costs. This suggests that an increase in rework rates is directly associated with higher rework and rework cost expenses. This finding underscores the significance of effective approaches to reducing rework rates, not only as a quality factor but also as a cost optimization strategy.

4.1.2 Associations between Process Efficiency and Time

A more detailed analysis unveiled an inverse association ($r = -0.63$, $p < 0.05$) between the Inspection Process Efficiency indicator from Group 3: Process Efficiency. And the Average Rework Tim" indicator from Group 4: Time and Productivity. This suggests that more efficient inspection processes are linked to shorter rework times. A reduction in rework time, in turn, can expedite defect rectification and enhance operational effectiveness.

4.1.3 Impact of Average Rework Time on Defect Origin

Exploring the relationship between Group 4: Time and Productivity and Group 5: Defect Origin, a positive correlation ($r = 0.48$, $p< 0.05$) was identified between the Average Rework Time indicator and the Proportion of Internal/External Rework indicator. This indicates that an increase in average rework time is associated with a higher proportion of internally originated rework compared to externally originated rework. This underscores the significance of effectively addressing internal rework to mitigate average correction time.

4.1.4 Relationship between Primary Rework Cause and Effectiveness of Corrective Actions

Examining Group 6: Analysis and Classification, a significant correlation ($r = 0.57$, $p < 0.05$) was observed between the Primary Rework Cause indicator and the "Effectiveness of Corrective Actions" indicator. This highlights the importance of accurately identifying the root cause of rework, as it directly influences the effectiveness of implemented corrective actions. A meticulous analysis of causes will enable the formulation of targeted strategies to reduce specific rework instances.

4.2 Development of the Rework Reduction Index

In this phase, constructing the rework reduction index represents a pivotal step in our approach. Building upon previous analyses of the indicators and their interrelationships, our aim was to devise a comprehensive metric that effectively encapsulates the intricacies of reducing rework rates in the industrial sector.

The index's development entailed a weighted combination of the 17 indicators, reflecting their relative importance. Each indicator underwent preprocessing to uniformly represent its category's contribution. To achieve this, we applied transformations and normalizations, ensuring each indicator contributed equitably to the overall index.

Employing fuzzy logic, we employed membership functions to aggregate the individual contributions of indicators into a singular value representing the level of rework reduction. These membership functions were calibrated to mirror the weight of each indicator in the overall assessment. In doing so, we took into account the nature of interactions between indicator groups and their influences on rework rates.

Once all contributions were aggregated, we arrived at a rework reduction index ranging from (0 to 100), signifying the effectiveness of strategies implemented to mitigate rework in industrial processes. Higher values indicate better performance in rework reduction, while lower values indicate the need for revisiting and enhancing approaches.

It is noteworthy that the proposed index not only condenses indicator complexities into a single measure but also considers interactions and synergies among different operational aspects. This enables managers and quality professionals to obtain a comprehensive view of the current state of rework within the organization, facilitating informed decision-making for continuous improvement.

The creation of this index constitutes a significant stride toward a more holistic and pragmatic approach to rework reduction. It synthesizes multidimensional and intricate information into a comprehensible and actionable format, affording management teams a valuable tool for assessing and enhancing industrial quality performance.

After constructing the Rework Reduction Index, it is crucial to ensure the viability and reliability of this model. Therefore, the subsequent phase involves the evaluation and validation of the model in various scenarios. This stage encompasses everything from hypothetical tests designed to verify the model's functionality to precision assessments using simulated data. Obtaining reliable results in these tests is fundamental to ensure that the model is effective in predicting and reducing rework in industrial operations.

The enhancement of the Rework Reduction Index approach's feasibility and practicality entails a comprehensive examination, involving both hypothetical data testing and precision assessment. Ensuring the effectiveness and practical applicability of the model is of paramount importance for its successful implementation in industrial settings.

The initial phase of our testing regime involved hypothetical scenarios designed to activate all model rules. This systematic approach was undertaken to validate the model's functionality under ideal circumstances and ascertain whether all inference rules functioned as intended. Specific values were assigned to each model indicator to ensure the activation of all rules. The outcome of these tests conclusively affirmed the model's responsiveness in accordance with predefined expectations.

Subsequently, a precision assessment of the model was carried out utilizing simulated hypothetical data. Synthetic data pertaining to the Rework Reduction Index was generated, simulating hypothetical scenarios across multiple consecutive months. The model was employed to predict values based on this fictitious data. Comparative analysis was performed between the model's predictions and the generated hypothetical values, with performance metrics such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and other pertinent indicators computed.

The results stemming from these fabricated assessments are presented in Tables 2 and 3 below.

Table 2. Results of hypothetical data testing

Month	*Simulated Rework Reduction Index*	*Predicted Rework Reduction Index*
January	0.70	0.68
February	0.65	0.63
March	0.80	0.78
April	0.55	0.53
May	0.75	0.73
June	0.62	0.60

Table 3. Results of precision assessment

Metric	*Value*
Mean Absolute Error (MAE)	0.02
Mean Absolute Percentage Error (MAPE)	2.86%
Coefficient of Determination (R^2)	0.94

This hypothetical precision assessment is of paramount importance for the critical evaluation of the model's predictive capabilities, even under simulated circumstances. The obtained results facilitate the identification of areas that may necessitate model refinement, ultimately leading to increased precision and reliability.

4.2.1 Classification

The defuzzification stage plays a pivotal role in transforming fuzzy outputs into numerical values that can be readily understood and interpreted. In this study, we adopted a simplified approach to defuzzification using a linear equation to assign output values. The output of defuzzification represents the rework reduction index, a quantitative indicator of corrective action effectiveness.

For the construction of the Rework Rate Index, the membership function shown in Figure 3 evidences that it can be standardized to capture the greatest possible number of regions with uncertainties. The trapezoidal functions at the ends capture regions that somehow would not have a need to include these regions.

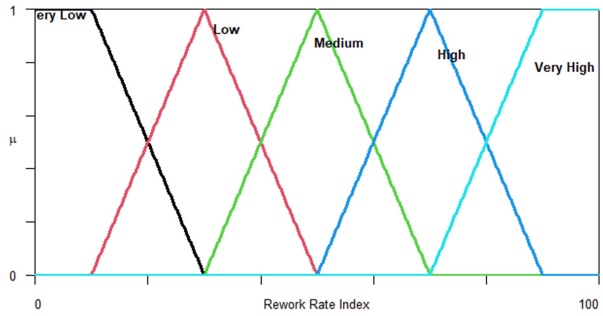

Figure 2. Membership functions for rework rate index

The fuzzy output resulting from prior stages comprises fuzzy sets associated with each linguistic term, representing various levels of rework reduction. To translate these fuzzy sets into a numerical value, the following linear defuzzification Equation 3.

$$y = \alpha\chi + \beta \tag{3}$$

Where:

a) y represents the output value after defuzzification, the rework reduction index.

b) χ is the centroid of the fuzzy set resulting from the inference stage, representing the degree of membership.

c) α is the angular coefficient of the equation, determined based on the range of output values and the possible range of values for χ.

d) β is the linear coefficient of the equation, adjusted to ensure correct mapping of output values.

For more intuitive interpretation and ease of understanding, output values are classified into five ranges, each associated with a descriptive linguistic term. These classification ranges are innovative and devised to directly reflect rework reduction effectiveness. The classification ranges and linguistic terms are listed in Table 4.

Table 4: Rework reduction index classification ranges

Classification	***Range***
Very Low	[0, 14]
Low	[14, 35]
Moderate	[35, 60]
High	[60, 78]
Very High	[78, 100]

The classification into ranges enables organizations to promptly grasp the impact of corrective action implementation, evaluating their performance contextually and offering a clear overall view of rework reduction effectiveness.

Utilizing a first-order output equation, coupled with range-based classification, simplifies result interpretation, making it accessible across all management levels and enabling informed decision-making for continuous improvements. While this approach is simpler compared to other defuzzification techniques, its simplicity is advantageous in terms of comprehension and practical application.

Here are some examples of how industries can make more effective use of the rework rate index:

Example 1: Quality Improvement (Defect and Scrap Rate)

An organization can utilize the Rework Reduction Index to identify critical areas for quality enhancement. Analysis of the indicators reveals that the "Rework Rate per Defect" consistently remains high, reaching 15. This indicates a prevalence of defects leading to rework. Upon further investigation into these defects, a significant proportion is found to occur during the assembly phase. In this scenario, the organization can implement targeted corrective measures, such as improving operator training during the assembly phase and introducing more rigorous quality verification protocols. This results in substantial improvements in product quality, leading to a significant reduction in the rework rate.

Example 2: Operational Efficiency (Related Costs)

Regarding operational efficiency, a company can employ the Rework Reduction Index to identify areas of inefficiency contributing to high operational costs due to rework. A detailed analysis of the indicators may highlight that the indicators "Rework Cost per Customer" reaches 25%, while "Reinspection Cost" records 30. Both exert a substantial impact on these costs. Upon deeper investigation, it may be revealed that many cases of rework are related to inadequate inspection processes and ineffective communication with customers regarding specific requirements. The organization can then revamp inspection procedures and improve communication with customers. This results in a significant reduction in rework costs and an improvement in operational efficiency.

Example 3: Informed Decision-Making (Process Efficiency)

The ongoing assessment of the Rework Reduction Index provides an objective foundation for strategic decision-making. Management can prioritize areas of intervention based on the analysis of indicators, allocate resources according to identified needs, and monitor progress over time. This results in more informed decisions aimed at improving industrial performance. For example, if the "Inspection Process Efficiency" indicator presents a value of 40, indicating unsatisfactory performance, management can allocate resources to optimize that specific process, resulting in efficiency gains.

Example 4: Proactive Management (Time and Productivity)

The Rework Reduction Index is not merely a static metric but rather a tool for continuous monitoring. This allows organizations to track their progress over time and adopt a proactive approach to identifying and addressing rework issues before they become more severe. For example, if the "Average Rework Time" indicator shows a value of 10, indicating a gradual increase over the months, the organization can take proactive measures, such as analyzing the underlying causes of this increase, to prevent the issue from worsening.

4.3 Discussions

The discussion of the results obtained through the application of the Rework Reduction Index has revealed valuable insights into management strategies and their impacts on rework reduction effectiveness in the industrial sector (Carvalho et al., 2019). In this section, we delve deep into the implications of the data generated using the fuzzy approach, emphasizing observed trends, challenges faced, and identified opportunities.

Analyzing the linguistically classified results has brought forth interesting patterns. We observed that strategies aligning with the Optimally Efficient and Satisfactorily Controlled categories showcase the success of implemented approaches (Rizvi et al., 2022). This indicates the effectiveness of rework management initiatives and suggests well-controlled processes.

Conversely, categories such as Moderately Reduced and Still Challenging point towards areas for continuous improvement. These classifications highlight opportunities for further enhancing management strategies, focusing on specific high-rework points (Amin et al., 2019). By understanding challenging areas, companies can target improvement efforts more precisely.

The analysis of correlations among different indicator groups also plays a pivotal role in result discussion. We noted that certain indicators are inherently related, mutually influencing each other. For instance, high inspection process efficiency (Group 3) may be positively correlated with reduced rework costs (Group 2). These correlations suggest that improvements in one indicator group can have significant impacts on other areas.

Furthermore, the results aggregated through fuzzy inference and defuzzification provide a comprehensive view of the combined impacts of indicators on the rework rate. This offers valuable insights into which indicators hold greater influence on the final classification and which areas can be prioritized for improvement actions.

During the discussion of results, acknowledging the challenges faced in applying the fuzzy methodology is also important. The inherent uncertainty in real-world data may result in classifications that may not be entirely precise. However, it is crucial to remember that fuzzy logic was chosen precisely to deal with this uncertainty and capture complex nuances present in the data.

Another challenge lies in selecting and defining the linguistic terms that make up the classification categories. While we have aimed to introduce innovative and descriptive terms, it is important to continuously assess whether these terms accurately capture the concepts they represent (Sharp et al., 2018).

Based on the result analyses, clear guidelines for improvement actions in the context of rework reduction can be derived. Strategies aligning with higher classification categories can be identified as best practices and benchmarks for other companies (Akhavan & Beckmann, 2017). Those falling within intermediate and lower categories offer opportunities for implementing specific improvements in identified challenging areas.

The discussion of results not only validates the effectiveness of the Rework Reduction Index but also provides fertile ground for informed decision-making, guiding companies to optimize efforts to achieve rework reduction goals and enhance process efficiency (Kurniawan et al., 2023).

Beyond identifying areas for improvement actions, the discussion of results also provides a solid foundation for the strategic implementation of rework reduction measures. Understanding which indicators have a greater impact on the final classification allows companies to allocate resources more effectively (Ravichandran, 2018). For instance, if analysis reveals that inspection process efficiency significantly influences the overall classification, companies can prioritize investments and innovations in this area for more substantial results (Kurniawan et al., 2023).

A comparative analysis between classifications obtained through the Rework Reduction Index and traditional performance metrics is also relevant in result discussion. While traditional metrics may provide an overview of rework in absolute numbers, the fuzzy index introduces a qualitative dimension that may unveil insights not captured by purely quantitative metrics. This comparison can display how qualitative and quantitative approaches complement each other, providing a more comprehensive picture of the state of rework reduction.

The implementation of the Rework Reduction Index is not limited to operational improvements alone. The discussion of results can also unveil insights into the impact of rework reduction strategies on organizational goals and vision. For example, an in-depth analysis can demonstrate how the effectiveness of corrective actions (Group 3) affects company reputation and customer satisfaction, with direct implications for marketing strategies and customer relationships.

It is important to emphasize that the discussion of results does not mark the end of the process. On the contrary, it offers a foundation for ongoing analysis and iterative feedback. As companies implement improvement measures based on classifications and insights obtained, it is essential to monitor and measure the outcomes of these actions. This completes the cycle of continuous improvement, where decisions are data-driven, actions are implemented, and results are evaluated, thus fueling a cyclical process of enhancement.

4.4 Practical Implications

The Rework Reduction Index offers several practical implications that can be applied in the industrial context to enhance operational efficiency, product quality, and decision-making processes. Adopting and implementing this index can provide organizations with the following benefits:

a) Quality Enhancement: The index provides a direct approach to improving the quality of industrial products. By analyzing areas with high rework rates, companies can identify the underlying causes of defects and implement specific corrective actions. This process results in higher-quality end products, reducing customer dissatisfaction and minimizing costs associated with defective products.

b) Operational Efficiency: The index also serves as an opportunity to optimize operational processes. By identifying correlations among indicators, organizations can understand how to improve efficiency at different stages of production. This allows for the precise allocation of resources and efforts, resulting in a more efficient and cost-effective operation.

c) Informed Decision-Making: Continuous evaluation of the index provides management teams with an objective basis for strategic decision-making. Managers can prioritize areas with the highest rework rates, allocate resources appropriately, and monitor progress over time. The result is more informed decision-making aimed at improving industrial performance.

d) Proactive Management: In addition to reflecting current performance, the index can be used proactively to predict and prevent future rework issues. By identifying trends, organizations can take preventive measures before problems escalate. This includes anticipating potential bottlenecks or critical areas that require immediate attention.

e) Benchmarking and Best Practices: By ranking organizations based on the index, companies can engage in benchmarking and identify best practices for rework reduction. This allows them to learn from other organizations that have achieved success in rework management and implement similar strategies to achieve positive outcomes.

f) Continuous Monitoring and Improvement: The index is not a static metric but rather a tool for continuous monitoring. This means that organizations can track their progress over time and assess the impact of corrective actions implemented. This continuous improvement cycle enables companies to adapt to changes in operational conditions and consistently focus on rework reduction.

5. Limitations and Future Opportunities

When considering the results obtained through the Rework Reduction Index and its application in evaluating rework management in the industrial sector, it is crucial to acknowledge its limitations while also exploring the opportunities this innovative approach can bring for future research.

5.1 Limitations

a) Data Quality: It is important to highlight that the accuracy and reliability of the classifications generated by the index are inherently tied to the quality of the input data used. Inaccurate, outdated, or incomplete data can compromise the accuracy of the analyses and, consequently, the classifications assigned to different indicators.

b) Subjectivity and Uncertainty: The very nature of fuzzy logic involves incorporating degrees of membership that reflect subjectivities and uncertainties. This implies that different experts might assign varying degrees of membership to the same indicators, resulting in variations in the obtained classifications.

5.2 Future Opportunities

To solidify the effectiveness of the Rework Reduction Index, conducting empirical studies in various industrial contexts is essential. Comparing the results obtained through the index with traditional rework metrics will allow for the verification of its practical applicability and alignment with operational reality. Furthermore, beyond the indicators already considered in this study, expanding the scope to include external factors such as seasonal variations, regulatory changes, and economic fluctuations can further enhance the analysis. This offers a more comprehensive understanding of the underlying causes of rework.

Lastly, performing comparisons between different companies or sectors can unveil insightful perspectives on best practices for rework reduction. This approach facilitates the identification of gaps and learning opportunities among organizations.

6. Conclusion

The development and application of the Rework Reduction Index represent a significant step toward improving quality management and efficiency in the industrial sector. This research aimed to address the challenges inherent in the complexity of industrial processes and the need to deal with data uncertainty and subjectivity, presenting an innovative approach based on fuzzy logic. The obtained results not only reflect the effectiveness of the proposed index but also highlight its ability to provide valuable insights to organizations in their continuous pursuit of operational excellence.

The detailed analysis of the 17 indicators grouped into different categories provided a holistic view of the factors contributing to rework in the industrial environment. The evaluation of correlation between these indicators, through Pearson correlation analyses, revealed intricate patterns of interdependence, indicating the multifaceted influence that factors can have on the rework rate. These findings reinforce the importance of an integrated approach to rework management rather than isolated solutions.

Fuzzy modeling proved to be an effective tool in handling the uncertainty and subjectivity present in industrial data. Defining fuzzy sets, membership functions, and inference rules enabled the transformation of quantitative and qualitative data into comprehensible and actionable classifications. The final output of defuzzification, represented on a scale from 0 to 100, with five innovative classification classes, provides a visually intuitive metric for rework assessment.

Ultimately, the Rework Reduction Index stands as a powerful tool to guide informed decision-making regarding rework management in the industrial sector. As organizations seek to optimize their processes and enhance product quality, this innovative approach has the potential to play a crucial role in achieving their goals.

6.1 Contributions to the Industrial Sector

This study lays a solid foundation for future developments in the field of quality management and efficiency in the industrial sector. Several directions can be explored to enhance the proposed approach and expand its impact on industrial sectors, such as:

i. Quality Enhancement: By providing a clear and comprehensive metric of the rework rate, organizations can identify areas for improvement and implement targeted corrective actions, resulting in higher-quality end products.

ii. Operational Efficiency: Analyzing correlations among indicators allows for more precise optimization of industrial processes, saving time and resources by reducing unnecessary rework.

iii. Informed Decisions: The index offers an objective basis for strategic decision-making, enabling managers to set priorities, allocate resources appropriately, and track progress over time.

iv. Proactive Management: With the ability to predict potential rework issues, organizations can adopt a proactive approach, minimizing risks and maximizing efficiency.

v. Benchmarking and Best Practices: Ranking organizations in terms of rework rate enables benchmarking and the identification of best practices, promoting knowledge dissemination across sectors.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Canadian Center of Science and Education.

The journal and publisher adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

References

Abdel-Tawab, K., & Noor, A. K. (1999). Uncertainty analysis of welding residual stress fields. *Computer Methods in Applied Mechanics and Engineering*, *179*(3-4), 327-344. https://doi.org/10.1016/S0045-7825(99)00045-6

Abe, S. (2000). *Pattern Classification. Neuro-Fuzzy Methods and Their Comparison* (1st ed.).

Abu, F., Gholami, H., Mat Saman, M. Z., Zakuan, N., & Streimikiene, D. (2019). The implementation of lean manufacturing in the furniture industry: A review and analysis on the motives, barriers, challenges, and the applications. *Journal of Cleaner Production*, *234*, 660-680. https://doi.org/10.1016/j.jclepro.2019.06.279

Akhavan, R. M., & Beckmann, M. (2017). A configuration of sustainable sourcing and supply management strategies. *Journal of Purchasing and Supply Management*, *23*(2), 137-151. https://doi.org/10.1016/j.pursup.2016.07.006

Akhigbe, I., Munir, K., Akinade, O., Akanbi, L., & Oyedele, L. O. (2021). Iot technologies for livestock management: A review of present status, opportunities, and future trends bernard. *Big Data and Cognitive Computing*, *5*(1). https://doi.org/10.3390/bdcc5010010

Alkan, B., & Harrison, R. (2019). A virtual engineering based approach to verify structural complexity of component-based automation systems in early design phase. *Journal of Manufacturing Systems*, *53*(September), 18-31. https://doi.org/10.1016/j.jmsy.2019.09.001

Amin, A. N. M., Mahmood, W. H. W., & Kamat, S. R. (2019). Lean practices for waste prioritising in machining based product. *International Journal of Mechanical and Production Engineering Research and Development*, *9*(5), 305-318. https://doi.org/10.24247/ijmperdoct201926

Baba, A. O., Liu, G., & Chen, X. (2020). Classification and Evaluation Review of Maximum Power Point Tracking Methods. *Sustainable Futures*, *2*(April), 100020. https://doi.org/10.1016/j.sftr.2020.100020

Banaeian, N., Mobli, H., Fahimnia, B., Nielsen, I. E., & Omid, M. (2018). Green supplier selection using fuzzy group decision making methods: A case study from the agri-food industry. *Computers and Operations Research*, *89*, 337-347. https://doi.org/10.1016/j.cor.2016.02.015

Battesini, M., Ten Caten, C. S., & Pacheco, D. A. De J. (2021). Key factors for operational performance in manufacturing systems: Conceptual model, systematic literature review and implications. *Journal of Manufacturing Systems*, *60*(June), 265-282. https://doi.org/10.1016/j.jmsy.2021.06.005

Büyüközkan, G., Karabulut, Y., & Arsenyan, J. (2017). RFID service provider selection: An integrated fuzzy MCDM approach. *Measurement: Journal of the International Measurement Confederation*, *112*(August), 88-98. https://doi.org/10.1016/j.measurement.2017.08.018

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. da P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers and Industrial Engineering*, *137*(August), 106024. https://doi.org/10.1016/j.cie.2019.106024

Chanamool, N., & Naenna, T. (2016). Fuzzy FMEA application to improve decision-making process in an emergency department. *Applied Soft Computing Journal*, *43*, 441-453. https://doi.org/10.1016/j.asoc.2016.01.007

Cortés, D., Ramírez, J., Ponce, P., & Molina, A. (2021). S3 manufacturing process taxonomy. *Journal of Manufacturing Processes*, *67*(October 2020), 579-610. https://doi.org/10.1016/j.jmapro.2021.04.069

dos Santos, A. R., Paterlini, E. M., Fiedler, N. C., Ribeiro, C. A. A. S., Lorenzon, A. S., Domingues, G. F., Marcatti, G. E., de Castro, N. L. M., Teixeira, T. R., dos Santos, G. M. A. D. A., Juvanhol, R. S., Branco, E. R. F., Mota, P. H. S., da Silva, L. G., Pirovani, D. B., de Jesus, W. C., Santos, A. C. de A., Leite, H. G., & Iwakiri, S. (2017). Fuzzy logic applied to prospecting for areas for installation of wood panel industries. *Journal of Environmental Management*, *193*, 345-359. https://doi.org/10.1016/j.jenvman.2017.02.049

Elkington, J. (1999). *Cannibals with Forks: the TBL of the 21st Century Business* (1st ed.).

Farahani, S., Khade, V., Basu, S., & Pilla, S. (2022). A data-driven predictive maintenance framework for injection molding process. *Journal of Manufacturing Processes*, *80*(January), 887-897. https://doi.org/10.1016/j.jmapro.2022.06.013

Franco, L. A., Rouwette, E. A. J. A., & Korzilius, H. (2016). Different paths to consensus? the impact of need for closure on model-supported group conflict management. *European Journal of Operational Research*, *249*(3), 878-889. https://doi.org/10.1016/j.ejor.2015.06.056

Gholizadeh, H., Fazlollahtabar, H., & Khalilzadeh, M. (2020). A robust fuzzy stochastic programming for sustainable procurement and logistics under hybrid uncertainty using big data. *Journal of Cleaner Production*, *258*, 120640. https://doi.org/10.1016/j.jclepro.2020.120640

Govindan, K., Paam, P., & Abtahi, A. R. (2016). A fuzzy multi-objective optimization model for sustainable reverse logistics network design. *Ecological Indicators*, *67*, 753-768. https://doi.org/10.1016/j.ecolind.2016.03.017

Hanif, M., Shah, A. H., Shah, I., & Mumtaz, J. (2023). Optimization of Bead Geometry during Tungsten Inert Gas Welding Using Grey Relational and Finite Element Analysis. *Materials*, *16*(10). https://doi.org/10.3390/ma16103732

Hasan, A. S. M. M., & Trianni, A. (2020). A review of energy management assessment models for industrial energy efficiency. *Energies*, *13*(21). https://doi.org/10.3390/en13215713

Ikumapayi, O. M., Akinlabi, E. T., Mwema, F. M., & Ogbonna, O. S. (2019). Six sigma versus lean manufacturing - An overview. *Materials Today: Proceedings*, *26*, 3275-3281. https://doi.org/10.1016/j.matpr.2020.02.986

Jiang, W., Xie, C., Zhuang, M., & Tang, Y. (2017). Failure mode and effects analysis based on a novel fuzzy evidential method. *Applied Soft Computing*, *57*, 672-683. https://doi.org/10.1016/j.asoc.2017.04.008

Karatop, B., Kubat, C., & Uygun, Ö. (2015). Talent management in manufacturing system using fuzzy logic approach. *Computers and Industrial Engineering*, *86*, 127-136. https://doi.org/10.1016/j.cie.2014.09.015

Karmaker, C. L., Aziz, R. Al, Palit, T., & Bari, A. B. M. M. (2023). Analyzing supply chain risk factors in the small and medium enterprises under fuzzy environment: Implications towards sustainability for emerging economies. *Sustainable Technology and Entrepreneurship*, *2*(1), 100032. https://doi.org/10.1016/j.stae.2022.100032

Kozarević, S., & Puška, A. (2018). Use of fuzzy logic for measuring practices and performances of supply chain. *Operations Research Perspectives*, *5*(June), 150-160. https://doi.org/10.1016/j.orp.2018.07.001

Kravchenko, M., Pigosso, D. C., & McAloone, T. C. (2019). Towards the ex-ante sustainability screening of circular economy initiatives in manufacturing companies: Consolidation of leading sustainability-related performance indicators. *Journal of Cleaner Production*, *241*, 118318. https://doi.org/10.1016/j.jclepro.2019.118318

Kurniawan, T. A., Meidiana, C., Dzarfan Othman, M. H., Goh, H. H., & Chew, K. W. (2023). Strengthening waste recycling industry in Malang (Indonesia): Lessons from waste management in the era of Industry 4.0. *Journal of Cleaner Production*, *382*(May 2022), 135296. https://doi.org/10.1016/j.jclepro.2022.135296

Lee, T., & Wakefield-Rann, R. (2021). Conspicuous and inconspicuous repair: A framework for situating repair in relation to consumer practices and design research. *Journal of Cleaner Production*, *294*. https://doi.org/10.1016/j.jclepro.2021.126310

Li, C., Chen, Y., & Shang, Y. (2022). A review of industrial big data for decision making in intelligent manufacturing. *Engineering Science and Technology, an International Journal*, *29*, 101021. https://doi.org/10.1016/j.jestch.2021.06.001

Malek, J., & Desai, T. N. (2020). A systematic literature review to map literature focus of sustainable manufacturing. *Journal of Cleaner Production*, *256*, 120345. https://doi.org/10.1016/j.jclepro.2020.120345

Mousavi, S. M., Mirdamadi, S., Siadat, A., Dantan, J., & Tavakkoli-Moghaddam, R. (2015). An intuitionistic fuzzy grey model for selection problems with an application to the inspection planning in manufacturing firms. *Engineering Applications of Artificial Intelligence*, *39*, 157-167. https://doi.org/10.1016/j.engappai.2014.12.004

Musteen, M. (2016). Behavioral factors in offshoring decisions: A qualitative analysis. *Journal of Business Research*, *69*(9), 3439-3446. https://doi.org/10.1016/j.jbusres.2016.01.042

Perera, A. T. D., & Kamalaruban, P. (2021). Applications of reinforcement learning in energy systems. *Renewable and Sustainable Energy Reviews*, *137*(October 2020), 110618. https://doi.org/10.1016/j.rser.2020.110618

Psarommatis, F., & Kiritsis, D. (2022). A hybrid Decision Support System for automating decision making in the event of defects in the era of Zero Defect Manufacturing. *Journal of Industrial Information Integration*, *26*, 100263. https://doi.org/10.1016/j.jii.2021.100263

Ragab, A., El Koujok, M., Ghezzaz, H., Amazouz, M., Ouali, M. S., & Yacout, S. (2019). Deep understanding in industrial processes by complementing human expertise with interpretable patterns of machine learning. *Expert Systems with Applications*, *122*, 388-405. https://doi.org/10.1016/j.eswa.2019.01.011

Ravichandran, T. (2018). Exploring the relationships between IT competence, innovation capacity and organizational agility. *Journal of Strategic Information Systems*, *27*(1), 22-42. https://doi.org/10.1016/j.jsis.2017.07.002

Rissman, J., Bataille, C., Masanet, E., Aden, N., Morrow, W. R., Zhou, N., Elliott, N., Dell, R., Heeren, N., Huckestein, B., Cresko, J., Miller, S. A., Roy, J., Fennell, P., Cremmins, B., Koch Blank, T., Hone, D., Williams, E. D., de la Rue du Can, S., … Helseth, J. (2020). Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070. *Applied Energy*, *266*(November 2019), 114848. https://doi.org/10.1016/j.apenergy.2020.114848

Rizos, V., Behrens, A., van der Gaast, W., Hofman, E., Ioannou, A., Kafyeke, T., Flamos, A., Rinaldi, R., Papadelis, S., Hirschnitz-Garbers, M., & Topi, C. (2016). Implementation of circular economy business models by small and medium-sized enterprises (SMEs): Barriers and enablers. *Sustainability (Switzerland)*, *8*(11). https://doi.org/10.3390/su8111212

Rizvi, M., Pratap, B., & Singh, S. B. (2022). Optimal energy management in a microgrid under uncertainties using novel hybrid metaheuristic algorithm. *Sustainable Computing: Informatics and Systems*, *36*(October

2021), 100819. https://doi.org/10.1016/j.suscom.2022.100819

Schumacher, A., Erol, S., & Sihn, W. (2016). A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises. *Procedia CIRP*, *52*, 161-166. https://doi.org/10.1016/j.procir.2016.07.040

Seth, D., & Rastogi, S. (2019). Application of vendor rationalization strategy for manufacturing cycle time reduction in engineer to order (ETO) environment: A case study. *Journal of Manufacturing Technology Management*, *30*(1), 261-290. https://doi.org/10.1108/JMTM-03-2018-0095

Shafiq, S. I., Sanin, C., Szczerbicki, E., & Toro, C. (2015). Virtual engineering object/virtual engineering process: A specialized form of cyber physical system for industrie 4.0. *Procedia Computer Science*, *60*(1), 1146-1155. https://doi.org/10.1016/j.procs.2015.08.166

Sharp, M., Ak, R., & Hedberg, T. (2018). A survey of the advancing use and development of machine learning in smart manufacturing. *Journal of Manufacturing Systems*, *48*, 170-179. https://doi.org/10.1016/j.jmsy.2018.02.004

Shen, N., Liao, H., Deng, R., & Wang, Q. (2019). Different types of environmental regulations and the heterogeneous influence on the environmental total factor productivity: Empirical analysis of China's industry. *Journal of Cleaner Production*, *211*, 171-184. https://doi.org/10.1016/j.jclepro.2018.11.170

Shen, Y. C., Chen, P. S., & Wang, C. H. (2016). A study of enterprise resource planning (ERP) system performance measurement using the quantitative balanced scorecard approach. *Computers in Industry*, *75*, 127-139. https://doi.org/10.1016/j.compind.2015.05.006

Sugeno, M. (1985). An introductory survey of fuzzy control. *Information Sciences*, *36*(1-2), 59-83. https://doi.org/10.1016/0020-0255(85)90026-X

Suryawanshi, P., & Dutta, P. (2022). Optimization models for supply chains under risk, uncertainty, and resilience: A state-of-the-art review and future research directions. *Transportation Research Part E: Logistics and Transportation Review*, *157*(December 2021). https://doi.org/10.1016/j.tre.2021.102553

Trianni, A., Cagno, E., & Farné, S. (2016). Barriers, drivers and decision-making process for industrial energy efficiency: A broad study among manufacturing small and medium-sized enterprises. *Applied Energy*, *162*, 1537-1551. https://doi.org/10.1016/j.apenergy.2015.02.078

Tyagi, S., Choudhary, A., Cai, X., & Yang, K. (2015). Value stream mapping to reduce the lead-time of a product development process. *International Journal of Production Economics*, *160*, 202-212. https://doi.org/10.1016/j.ijpe.2014.11.002

Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. *Journal of Manufacturing Systems*, *48*, 144-156. https://doi.org/10.1016/j.jmsy.2018.01.003

Willems, L. L., & Vanhoucke, M. (2015). Classification of articles and journals on project control and earned value management. *International Journal of Project Management*, *33*(7), 1610-1634. https://doi.org/10.1016/j.ijproman.2015.06.003

Zadeh, L. A. (1978). Fuzzy sets as a basis for a theory of possibility* l.a. zadeh. *Fuzzy Sets and Systems*, *1*(1), 3-28.

Zeng, J., Anh Phan, C., & Matsui, Y. (2015). The impact of hard and soft quality management on quality and innovation performance: An empirical study. *International Journal of Production Economics*, *162*, 216-226. https://doi.org/10.1016/j.ijpe.2014.07.006

Zhang, X., & Mahadevan, S. (2017). Aircraft re-routing optimization and performance assessment under uncertainty. *Decision Support Systems*, *96*, 67-82. https://doi.org/10.1016/j.dss.2017.02.005

Zimmermann, H. J. (2001). *Fuzzy set and Theory* (4th ed., Vol. 4). https://doi.org/10.1007/978-94-010-0646-0