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An Analysis and Design of Adaptive Assessment System for Manufacturing Industry 4.0 Implementation in Indonesia

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Abstract. The implementation of Industry 4.0 technology has developed rapidly. Despite its development, Indonesia is still nascent and requires some implementation monitoring in its priority industries. This study aims to design a system for assessing the readiness of implementing Industry 4.0 in priority manufacturing industries in Indonesia. A Fuzzy Inference System framework with six main dimensions has been developed to assess the level of readiness for Industry 4.0 in priority manufacturing industries. The six assessment dimensions are Legal Consideration, Products and Service, Manufacturing and Operations, Strategy and Organization, Supply Chain, and Business Model. These dimensions have been developed into a complete assessment system for evaluating the level of readiness for implementing Industry 4.0. Validation of the system has shown that the multi-dimensional assessment system can provide appropriate assessment results to assess the level of readiness for Industry 4.0 in priority manufacturing industries.

1 Introduction

The manufacturing industry plays an important role in Indonesia's economy, providing a proportion of the value added to the gross domestic product (GDP) of up to 20.61% in 2020 and an average growth rate of 4% in 2015-2019 [1,2]. The Indonesian manufacturing industry is also challenged to contribute more to the GDP during the Industry 4.0 revolution, including a contribution of up to 30% to the GDP, job creation, and increasing net exports by up to 10% [3]. This is certainly a challenge for the manufacturing industry, which is required to compete globally with more efficient operations.

The implementation of Industry 4.0 in the manufacturing industry offers tremendous potential for increasing contributions to the GDP and economic resilience. Industry 4.0 can enhance competitiveness and provide more stable and sustainable business operations, integrating manufacturing with consumers and other stakeholders, and aligning with sustainable development goals [4] [5]. However, despite the enormous opportunities, Indonesia is still at the nascent level or the lowest level of readiness in implementing Industry 4.0 according to [6]. On the other hand, other countries in the ASEAN region have reached the Leading criteria or are already ready to implement Industry 4.0.

The lack of readiness in implementing the Industry 4.0 revolution is a major issue that needs to be addressed immediately. To achieve the grand goals, a strategy is needed for accelerating the implementation of Industry 4.0 in priority manufacturing industries in Indonesia. Before formulating such a strategy, a mapping of the capabilities of priority manufacturing industries in implementing Industry 4.0 is necessary. The mapping of readiness for implementing Industry 4.0 in priority manufacturing industries is the first stage to determine the strategy for accelerating the implementation of Industry 4.0 in achieving Indonesia's competitiveness and economic resilience goals by 2030 [7].

Previous research has proposed various methods for assessing the readiness of implementing Industry 4.0. [8] proposed measuring Industry 4.0 readiness through the supply chain operation reference (SCOR) approach and a Likert assessment. [9] designed a performance assessment system for the industry using a combination of qualitative and quantitative approaches. [10,11] designed assessment systems using a fuzzy approach. In addition to assessment models, previous research has proposed several indicators for assessing Industry 4.0 readiness, including [12], who proposed 9 dimensions for assessing Industry 4.0 readiness in manufacturing; [13], who proposed dimensions of technology, culture, and organization in assessing the readiness of implementing Industry 4.0; and [14], who proposed six dimensions for assessing Industry 4.0 readiness, with the technology dimension being the most important.

Previous research has developed several models for assessing the readiness model to implementing Industry 4.0, but in the case of Indonesia, appropriate indicators and assessment dimensions are required. In addition, differences in perceptions of assessment dimensions and indicators are also a major problem that needs to be addressed immediately. These differences in perception will have an impact on inaccurate assessment models,

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which will further pose a threat to the implementation of Industry 4.0 in the manufacturing industry. This study proposes a fuzzy approach to assessing feasibility that can accommodate differences in assessments and perceptions, ambiguity, and vagueness [15] in measuring the level of industrial implementation [16] and [12] also suggest designing an Industry 4.0 readiness assessment model with qualitative and quantitative indicators to provide an adaptive assessment model, flexible, and able to map industrial capabilities.

This study aims to design an adaptive model to assess Industry 4.0 readiness for the priority industry in Indonesia. This model is also required to map the capability of the Indonesian manufacturing industry and provide further improvement strategies. A fuzzy approach is proposed for the adaptive system modeling to accommodate qualitative and quantitative indicators in Industry 4.0 readiness.

This paper is organized into four sections: in the first section, research motivation and background are explored. In the second section, the research stage and method are delivered in designing the systems to assess Industry 4.0 readiness. In the third section, the result and discussion are elaborated and the designed system is validated. Finally, the conclusion and recommendation are concluded in the study.

2 Method

2.1 Research stage

The research stage is depicted in Figure 1. In the first stage, the research motivation and research gap are explored. The industry 4.0 readiness models are analyzed and find its requirements for the manufacturing industry. In the next stage, the ultimate stage of the research, the indicators and dimensions are determined. Previous research provided many dimensions and indicators, while this research refers to which provides six dimensions and 37 indicators. In this research, to accommodate an adaptive assessment and to improve the assessment model the indicators are stated in qualitative and quantitative manners. This way is possible to increase model validity [17].

2.2 Data analysis and technique

This research provides a fuzzy inference system to (FIS) develop the Industry 4.0 readiness assessment for the manufacturing industry. The FIS model is organized into six main parts: crisp input, fuzzification, fuzzy rule modeling, aggregation, defuzzification, and crisp output. In the first stage, the crisp input is transformed into a fuzzy number. In this stage, this study provides a normalization technique.

Suppose that a_i as the actual performance of indicator i, u_c and U_c as lower and upper range performance of indicator i, and T_i as the target performance of indicator i, the normalization score that is transformed into fuzzy crisp for the lower and upper target are described in Equations 1 and 2.

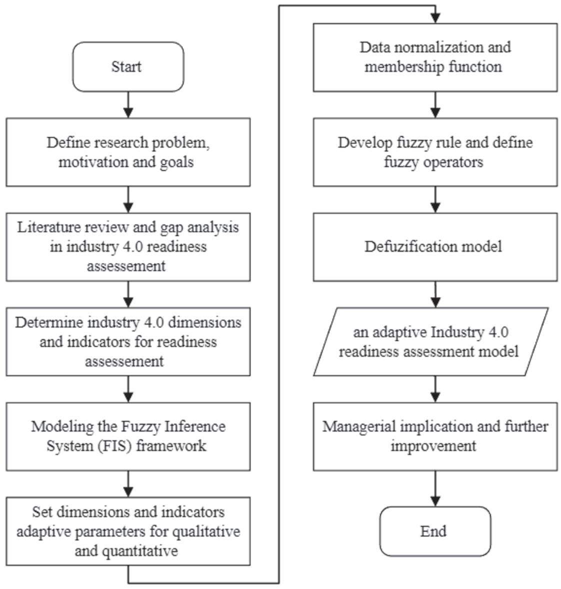

Fig.1. Research Stage

$$x_c = \begin{cases} \frac{a_i - u_i}{T_i - u_i}, & z_i \leq T_i \\ 1, & z_i \geq T_i \end{cases} \quad (1)$$

$$x_c = \begin{cases} 1, & z_i \leq T_i \\ \frac{U_i - a_i}{U_i - T_i}, & z_i \leq T_i \end{cases} \quad (2)$$

The fuzzy rule-based acquisition is the sensitive and hard part of FIS modeling. Fuzzy rules combination defines the crisp output. Expert judgment is required to verify the model. Despite the high number of indicators for each dimension, the fuzzy rules that should be generated by the expert are very high. In this stage, the expert knowledge acquisition will face difficulty to verify all rules, therefore this research applied a method proposed by [17,18] to generate the fuzzy rules.

3 Result and discussion

3.1 The need of industry 4.0 readiness modeling in Indonesia

The concept of Industry 4.0 has long been proposed as a new paradigm for improving industrial efficiency and productivity. The main concept of the Industry 4.0 approach is to create vertical and horizontal integration in the manufacturing system through digital integration and transformation throughout the production process [12]. In its development, not all industries can implement this approach, but the benefits are enormous for the progress of production and digital transformation.

To address the implementation of Industry 4.0 in the manufacturing industry, previous research has developed a system to demonstrate the industry's ability to utilize 4.0 technologies in the production process [19]. In another study, a system for assessing the readiness of the industry, known as a maturity model, was developed to indicate the state in which the industry is ready, complete, and capable of implementing Industry 4.0 in its production system [12]. With the development of technology, various models for assessing the readiness of implementing Industry 4.0 have been proposed, but there are still some aspects that need to be considered to determine the industry's ability comprehensively.

Considering the success of implementing Industry 4.0 technology in other Southeast Asian countries such as Malaysia and Singapore [6], Indonesia needs to consider looking into and implementing Industry 4.0 in potential industries. The main thing to do is to assess the level of readiness for Industry 4.0 in the Indonesian manufacturing industry. In assessing the industry's ability and readiness in implementing the Industry 4.0 approach, several numerical indicators need to be considered and grouped into dimensions for evaluating Industry 4.0 readiness. Some weaknesses found in formulating indicators and dimensions to assess Industry 4.0 readiness are descriptive assessments [13], assessments using Likert scales [12], and short surveys in the industry [20].

To address a more adaptive assessment that accommodates the uncertainty of indicators in the field and a more valid assessment, a more systematic approach is needed. The assessment indicators and dimensions need to consider qualitative and quantitative indicators so that the data collection process is more appropriate to the actual situation in the field. This is also suggested by [16] and [12] to design a model with a multi-methodology approach by acquiring quantitative and qualitative data, resulting in a more valid assessment of Industry 4.0 readiness.

Indonesia has also developed a framework for assessing Industry 4.0 readiness called the Indonesia Industry 4.0 Readiness Index (INDI 4.0). INDI 4.0 is a reference index used by industry and the government to assess the level of readiness of industries towards Industry 4.0. INDI is structured around five pillars and 17 fields, namely factory operations, management and organization, people and culture, products and services, and technology [21]. INDI 4.0 is assessed using a Likert scale of 0-4 through an online survey of relevant industries. However, INDI 4.0 does not yet cover all aspects that need to be considered in Industry 4.0 readiness, such as supply chain systems and business process models.

3.2 Proposed industry 4.0 dimensions and indicators

This study proposes different indicators and assessment dimensions from those proposed in INDI 4.0. The assessment framework for Industry 4.0 readiness adopts the evaluation system developed by [22], called the Industry 4 Readiness Assessment Tools. The framework has been validated globally by related industries. This is an opportunity to validate the framework in the priority industry in Indonesia with a new model of assessment.

The dimensions considered in this assessment model are legal considerations, products and services, manufacturing and operations, strategy and organizations, supply chain, and business model. The dimensions and indicators are provided in Table 1. Target u_i and Ui refer to Equation 1 as the lower and upper target of indicator *i*.

3.3 FIS modeling for industry 4.0 readiness

Figure 2 illustrates the overall structure of the model. The model utilizes a FIS-based approach to generate a clear output related to the performance of industry 4.0 dimensions. The data acquisition stage is crucial for managing data analysis and processing. Two types of data are suggested: qualitative data, which is obtained from expert judgments and includes linguistic labels that may vary across experts, and quantitative data, which is collected from secondary sources and supplemented with benchmark data. The qualitative and quantitative datasets are processed using Equations 1 and 2 concerning data targets (U_i and u_i). To handle the variability in expert opinions, an ordered weighted average model is proposed to generate a single linguistic label [23].

Fuzzy rules are developed to transform crisp input into output. The number of fuzzy rules is determined by the number of indicators (N) and linguistic levels (l), as explained in Equation 3. For instance, as dimensions have four indicators and set three linguistic levels, then the number of rules that must be developed is 81 rules, and so on. The same calculation applies to other cases as well.

$$Number\ of\ rules = \prod_{l=1}^{L} N_l \tag{3}$$

Although it may be challenging for experts to develop a large number of rules, this research offers a solution by utilizing a rule generator proposed by Phillis et al. (2011). The generator operates in two steps: first, it converts linguistic labels into integer values (e.g., low, moderate, and high are transformed into 1, 2, and 3, respectively). Second, the dependent part of the generated rules is expressed in these transformed values and then summed up to produce a total score. This total score is used as the consequent part of the rules and is mapped to a specific range, as follows:

$$Consequent\ parts = \begin{cases} Low; & if\ 4 \le total\ score \le 7 \\ Moderate; & if\ 8 \le total\ score \le 10 \\ High; & if\ 11 \le total\ score \le 12 \end{cases}$$

Table 1. Dimensions and indicators for industry 4.0 readiness in the manufacturing company.

No	Dimensions	Indicators	Unit	Target
1	Legal consideration	1. Contracting models	Qualitative	U_i
		2. Risk	Quantitative	u_i
		3. Data protection	Qualitative	U_i
		4. Intellectual property	Quantitative	U_i
2	Products and service	1. Product customization	Quantitative	U_i
		2. Digital features of products	Quantitative	U_i
		3. Data-driven services	Quantitative	U_i
		4. Level of product data usage	Quantitative	U_i
		5. Share of revenue	Quantitative	U_i
3	Manufacturing and operations	1. Automation	Quantitative	U_i
		2. Machine and operation system integration	Quantitative	U_i
		3. Digital modeling	Quantitative	U_i
		4. Operation data collection and usage	Quantitative	U_i
		5. Cloud solution usage	Quantitative	U_i
		6. IT and data security	Quantitative	U_i
4	Strategy and organization	1. Degree of strategy implementation	Quantitative	U_i
		2. Investments and finance	Quantitative	U_i
		3. People capabilities	Quantitative	U_i
		4. Collaboration	Quantitative	U_i
		5. Leadership	Quantitative	U_i
5	Supply chain	1. Inventory control using real-time data management	Quantitative	U_i
		2. Supply chain integration	Quantitative	U_i
		3. Supply chain visibility	Quantitative	U_i
		4. Supply chain flexibility	Quantitative	U_i
		5. Lead times	Quantitative	u_i
6	Business model	1. 'As a service' business model	Qualitative	u_i
		2. Real-time tracking and automated scheduling	Qualitative	u_i
		3. Integrated marketing channels	Qualitative	U_i
		4. Data-driven decisions	Qualitative	U_i
		5. IT-supported business	Quantitative	U_i

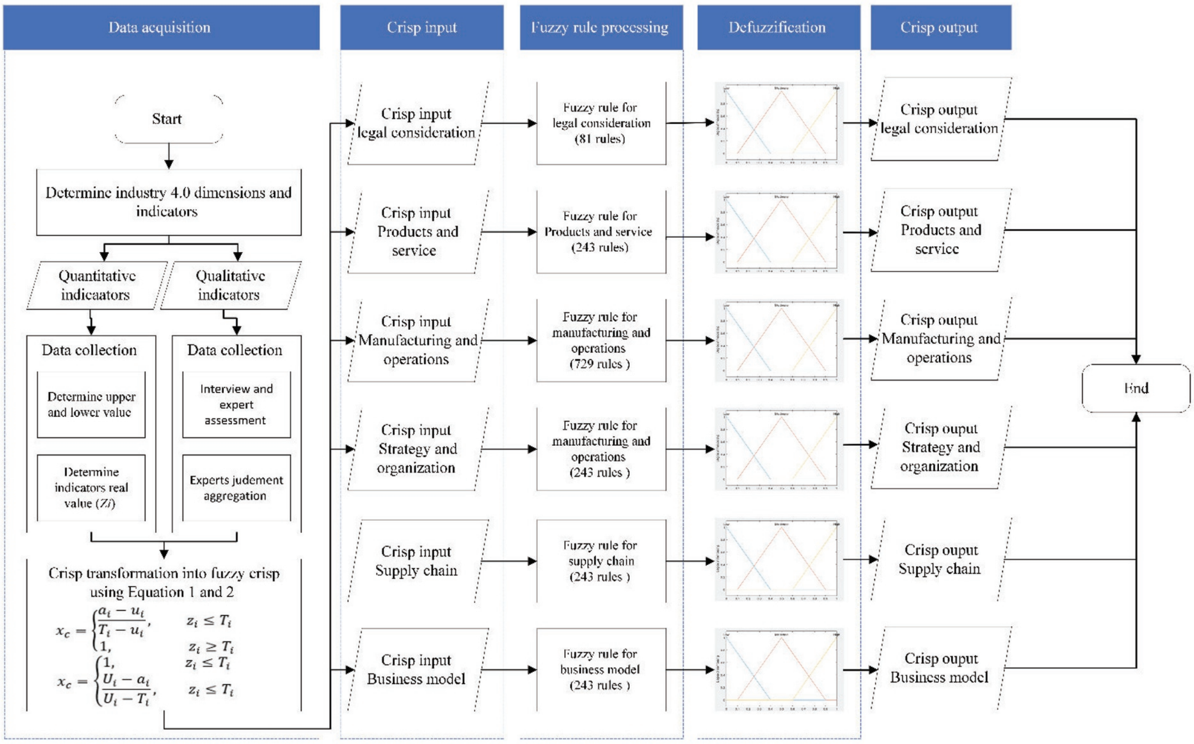

Fig. 2. General model framework of industry 4.0 readiness assessment

The range of consequent parts varies for each dimension based on the number of input and output variables and linguistic labels involved. As an example, the combination of the rule for the legal consideration dimension is provided in Table 2.

1. If (ConstractingModel is Low) and (Risk is Low) and (DataProtection is Low) and (IntellectualProperty is Low) then (Performance is Low) (1)
2. If (ConstractingModel is Low) and (Risk is Low) and (DataProtection is Low) and (IntellectualProperty is Moderate) then (Performance is Low) (1)
3. If (ConstractingModel is Low) and (Risk is Low) and (DataProtection is Low) and (IntellectualProperty is High) then (Performance is Low) (1)
4. If (ConstractingModel is Low) and (Risk is Low) and (DataProtection is Moderate) and (IntellectualProperty is Low) then (Performance is Low) (1)
5. If (ConstractingModel is Low) and (Risk is Low) and (DataProtection is Moderate) and (IntellectualProperty is Moderate) then (Performance is Low) (1)
6. If (ConstractingModel is Low) and (Risk is Low) and (DataProtection is Moderate) and (IntellectualProperty is High) then (Performance is Low) (1)
7. If (ConstractingModel is Low) and (Risk is Low) and (DataProtection is High) and (IntellectualProperty is Low) then (Performance is Low) (1)

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81. If (ConstractingModel is High) and (Risk is High) and (DataProtection is High) and (IntellectualProperty is High) then (Performance is High) (1)

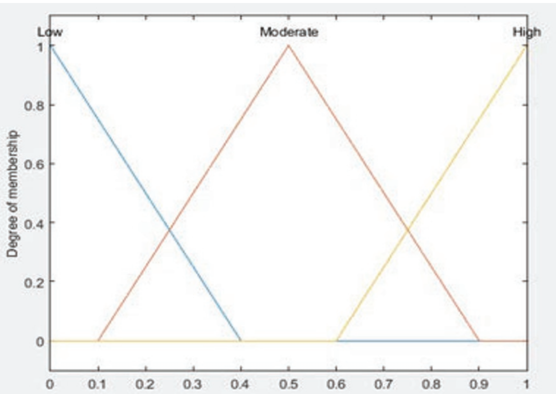

Fig. 3. Fuzzy scale for input and output variables

Table 2. FIS model parameter and operator

No.	Parameter	Operator
1	Fuzzy inference model	Mamdani
2	Membership function	Triangular Fuzzy Number
3	Rule Operator	And
4	Implication function	Min
5	Aggregation function	Max
6	Defuzzification function	Centroid

Fuzzy rules determine the dimensions of performance. The variable input is processed by the Mamdani fuzzy modeling using fuzzy rules then determine the performance with the centroid defuzzification model. Before the qualitative and quantitative data are normalized, it needs to determine its membership function (μ). The linguistic labels and their membership functions are identified and the fuzzy scales for input and output variables are depicted in Figure 3. Further, the general operator of the FIS model to assess the Industry 4.0 readiness of manufacture is shown in Table 2.

3.4 Data analysis and testing

A total of six dimensions were assessed using Fuzzy Inference Systems to evaluate the readiness of the manufacturing industry in adopting Industry 4.0 Technology, as illustrated in Figure 4. The developed model allows for the identification of the current performance of the manufacturing industry and potential areas for improvement. To demonstrate the model's effectiveness, hypothetical data were utilized in this study to identify the current manufacturing performance in terms of Industry 4.0 readiness, as shown in Table 3.

Six dimensions of readiness in Industry 4.0 have been tested. Using a randomized dataset, the assessment system enables us to provide the current manufacturing readiness in adopting Industry 4.0 transformation. The result of the assessment is provided in the table which the highest score is 1.00 while the lower score is 0.00. The result shows that the current readiness of the manufacturer in adopting Industry 4.0 is not satisfied. The highest score is only 0.556 which does not fulfill the highest readiness performance. Moreover, the result is only a hypothetical dataset that does not describe any current condition. Therefore, the model is possible to validate using a field observation dataset that involves experts and respondents from related industries.

Table 3. Model testing and verification.

No	Dimension	Indicators value	Result
1	Legal consideration	[0.50 0.08 0.64 0.24 0.0]	0.403
2	Product and service	[0.48 0.86 0.71 0.97 0.35]	0.556
3	Manufacturing and operations	[0.33 0.66 0.98 0.77 0.08 0.77]	0.530
4	Strategy	[0.74 0.45 0.26 0.28 1.00]	0.432
5	Supply chain	[0.81 0.99 0.83 0.09 0.44]	0.500
6	Business model	[0.15 0.85 0.18 0.59 0.78]	0.437

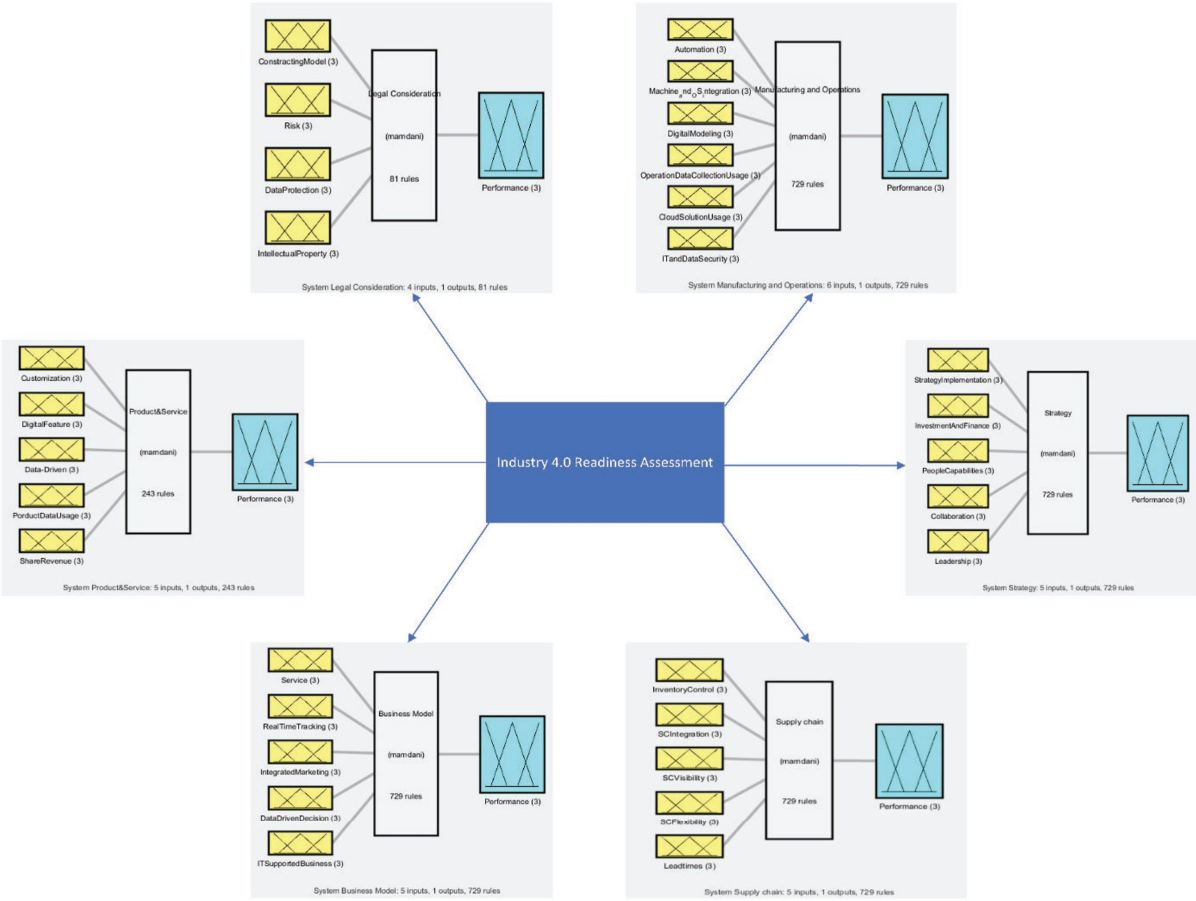

Fig. 4. Practical framework for Industry 4.0 readiness assessment

4 Conclusion

The Indonesian manufacturing industry is currently at a nascent stage and requires further improvement to fully adopt Industry 4.0. To identify the current performance of Indonesian manufacturing, an Industry 4.0 readiness assessment is necessary. This study proposes an adaptive model that accommodates multiple dimensions and indicators using both qualitative and quantitative data to monitor Industry 4.0 readiness in manufacturing companies. Six dimensions were selected for assessment, including Legal Consideration, Product and Service, Manufacturing and Operations, Strategy, Supply Chain, and Business Model. A fuzzy inference system with an adaptive model was developed to assess Industry 4.0 readiness and has proven effective in evaluating current performance and processing qualitative and quantitative datasets.

However, further research is necessary to apply the model using real datasets and develop a comprehensive model that consolidates all dimensions into a single score to monitor the current Industry 4.0 readiness level from multiple dimensions.

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References

[1] Badan Pusat Statistik, *Proporsi Nilai Tambah Sektor Industri Manufaktur Terhadap PDB,* https://www.bps.go.id/indikator/indikator/view_data/0000/data/1214/sdgs_9/1 (accessed February 3, 2022) (2020)

[2] Badan Pusat Statistik, *Nasional Indonesia. Perkembangan Beberapa Indikator Utama Sosial-Ekonomi Nasional*, https://www.bps.go.id/publication/2022/02/04/a108c0ac2a069aeb7f7af523/perkembangan-beberapa-indikator-utama-sosial-ekonomi-indonesia-november-2021.html (accessed February 3, 2022) (2021)

[3] Kemenperin. *Making Indonesia 4.0. Kementerian Perindustrian RI,* pp. 1–8 (2019)

[4] M. Man, S. Strandhagen, *An Industry 4.0 Research Agenda for Sustainable Business Models*, Procedia CIRP **63**, pp. 721–726 (2017).

[5] M. Manavalan, J. Jayakrishna, *A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements,* Computers and Industrial Engineering **127**, pp. 925–53 (2019)

[6] A. T. Kearney, *Accelerating 4IR in ASEAN: An Action Plan for Manufacturers* (2020).

[7] Kementerian Perindustrian, *Revolusi Industri 4.0 Indonesia,* Jakarta: Kementerian Perindustrian, (2018)

[8] L. Müller, K. Zeisler, S. Schirl, *A digital readiness check for the evaluation of supply chain aspects and company size for Industry 4.0*., Journal of Manufacturing Technology Management **33**, 9, pp. 1–18 (2021)

[9] A. Azevedo, S. Santiago, *Design of an assessment industry 4.0 maturity model: An application to manufacturing company*, Proc. Int. Conf. Ind. Eng. Oper. Manag **208** (2019)

[10] C. Scavarda, GI Nascimento and G Garza-Reyes. *A fuzzy rule-based industry 4.0 maturity model for operations and supply chain management*, International Journal of Production Economics **231,** pp. 1–21 (2021)

[11] M. Sadeghi, M. Mansouri, K. Kumar, *Developing an industry 4.0 readiness model using fuzzy cognitive maps approach*, International Journal of Production Economics **255**, 108658 (2023)

[12] S. Erol, S. Sihn, *A Maturity Model for Assessing Industry 4.0 Readiness and Maturity of Manufacturing Enterprises*, Procedia CIRP, **52**, pp. 161–1666 (2016)

[13] R. Rajnai, K Kocsis, *Assessing industry 4.0 readiness of enterprises,* 2018 IEEE 16th World Symp. Appl. Mach. Intell Informatics (2018)

[14] H. Soomro, A. Abdullah, Industry 4.0 readiness models: A systematic literature review of model dimensions, *Information (Switzerland)* **11,** 7, pp. 1–13 (2020)

[15] F. Zadeh, *Fuzzy Sets*, Information and Control **8**, pp. 338–353 (1965)

[16] C. Scavarda, G. I. Nascimento, G. Garza-Reyes, *A fuzzy rule-based industry 4.0 maturity model for operations and supply chain management*, International Journal of Production Economics **231** (2021)

[17] M. Yani, M. Marimin, M. Machfud, M. Asrol, E. Hambali, P. Papilo, S. Mursidah, *An Adaptive Fuzzy Multi-Criteria Model for Sustainability Assessment of Sugarcane Agroindustry Supply Chain*, IEEE Access **10**, 5497–517 (2022)

[18] G. Kouikoglou, Y. Phillis, *SAFE 2013: Sustainability of countries updated*, *Ecological* Indicators **38**, pp. 61–66 (2014)

[19] S. Jensen, P. Philipsen, H. Haug, *Drivers and barriers for industry 4.0 readiness and practice: A SME perspective with empirical evidence*, Proc. Annu. Hawaii Int. Conf. Syst. Sci., IEEE Computer Society, 5155 (2019)

[20] M. Winroth, C. A. Centerholt, H. Hallin, *Industry 4.0 readiness in manufacturing companies: Challenges and enablers towards increased digitalization*, Procedia CIRP, **81**, (2019)

[21] Kementrian Perindustrian RI, *Indonesia Industry 4.0 Readiness Index (Index Kesiapan Industri di Indonesia untuk Bertransformasi Menuju Industri 4.0).* Kementrian Perindustrian RI (2018*)*

[22] A. Agca, G. Godsell, I. W. Davis, X. Xu, *An Industry 4 readiness assessment tool*, The University of Warwick (2020)

[23] Y. Yager, *Non-numeric multi-criteria multi-person decision making*, Group Decision and Negotiation **2**, 1, pp. 81–93 (1993)