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Development of an Explainable Expert System for Smart Factory Readiness Assessment in Manufacturing Industries

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Abstract

Smart Factory adoption has become a critical strategy for manufacturing industries seeking to improve productivity, operational flexibility, and global competitiveness in the era of Industry 4.0. However, many organizations still lack a systematic, reliable, and transparent approach to evaluating their readiness for Smart Factory implementation. This study aims to develop an Expert System for determining industry readiness for Smart Factories by integrating expert knowledge and Explainable Artificial Intelligence (XAI). Expert knowledge was acquired through interviews with Industry 4.0 specialists, manufacturing practitioners, and automation experts, as well as an extensive literature review to identify readiness criteria related to technology, organization, human resources, processes, and financial capability. To enhance transparency and user trust, Explainable AI techniques were incorporated to provide interpretable explanations and feature contribution analyses for readiness recommendations. The system was validated through expert evaluation and case studies involving manufacturing organizations. The results indicate that the proposed system successfully classified organizations into five readiness levels and generated clear, understandable explanations for each recommendation. Validation findings demonstrated a high level of agreement between system outputs and expert assessments, confirming the reliability and practical applicability of the proposed approach. Furthermore, feature contribution analysis revealed that automation level, workforce digital skills, and IoT infrastructure were the most influential determinants of Smart Factory readiness.

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1. Introduction

The rapid advancement of digital technologies has transformed the manufacturing sector and accelerated the transition toward Industry 4.0(Kagermann, 2014). Industry 4.0 represents the fourth industrial revolution, characterized by the integration of advanced technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), Artificial Intelligence (AI), cloud computing, big data analytics, and industrial automation into manufacturing processes. These technologies enable the development of Smart Factories, where machines, systems, and humans communicate and collaborate in real time to optimize production efficiency, flexibility, quality, and decision-making. As global competition intensifies, manufacturing organizations are increasingly adopting Smart Factory initiatives to improve operational performance and maintain competitiveness in rapidly changing markets.

Despite the growing interest in Smart Factory implementation, many industries face significant challenges in determining whether they are adequately prepared for such a transformation(Sjödin et al., 2018). Smart Factory adoption requires substantial investments in technology infrastructure, workforce competencies, organizational culture, process integration, and strategic planning. Consequently, organizations must carefully evaluate their readiness before initiating digital transformation projects. A comprehensive readiness assessment helps identify strengths, weaknesses, opportunities, and gaps that may affect the success of Smart Factory implementation. Without a systematic evaluation process, organizations may encounter implementation failures, inefficient resource allocation, or resistance to technological change.

Assessing Smart Factory readiness, however, is a complex task(Jung et al., 2016). Readiness evaluation typically involves multiple dimensions, including technological capability, organizational preparedness, workforce skills, operational processes, and financial resources. These dimensions consist of numerous indicators that interact with one another, making the assessment process highly complex and multidimensional. In many cases, readiness evaluation relies heavily on expert judgment and experience, which may introduce subjectivity and inconsistencies in decision-making. Furthermore, existing assessment approaches often provide limited explanations regarding how readiness conclusions are generated, reducing transparency and stakeholder trust in the evaluation results.

To address these challenges, Expert Systems have emerged as a promising solution for supporting complex decision-making processes. An Expert System is a knowledge-based artificial intelligence system designed to emulate the reasoning process of human experts in solving domain-specific problems. By capturing expert knowledge and representing it through rules and inference mechanisms, Expert Systems can provide consistent, reliable, and scalable readiness assessments. In the context of Smart Factory adoption, an Expert System can assist organizations in evaluating their preparedness based on predefined criteria and expert-defined decision rules.

The growing adoption of Industry 4.0 technologies has encouraged researchers to develop various frameworks and assessment models to evaluate organizational readiness for Smart Factory implementation. Over the last decade, numerous studies have explored readiness assessment, maturity evaluation, expert knowledge integration, and explainable decision-support systems in manufacturing environments. One of the earliest and most influential studies was conducted by Andreas Schumacher, Selim Erol, and Wilfried Sihn (2016), who proposed a comprehensive Industry 4.0 maturity model for manufacturing enterprises. Their model introduced nine dimensions, including products, customers, operations, technology, strategy, leadership, governance, culture, and people, to assess organizational readiness for Industry 4.0 transformation. The study emphasized that successful Smart Factory implementation requires not only technological readiness but also organizational preparedness and strategic alignment. The model has since become a widely referenced framework for Industry 4.0 readiness assessment.

In the same year, Kiwook Jung, Boonserm Kulvatunyou, Sangsu Choi, and Michael Brundage (2016) developed a Smart Manufacturing System Readiness Assessment framework aimed at helping manufacturers evaluate their preparedness for adopting smart manufacturing technologies. Their research demonstrated that readiness assessment can assist organizations in prioritizing technology investments and identifying areas requiring improvement before implementing Smart Factory initiatives. Furthermore, the study found a positive relationship between readiness levels and operational performance, highlighting the practical value of readiness assessment tools.

As Industry 4.0 research matured, scholars began to investigate the diversity of readiness models available in the literature. Hizam-Hanafiah, Soomro, and Abdullah (2020) conducted a systematic literature review of Industry 4.0 readiness models and analyzed 97 studies published between 2000 and 2019. Their review identified 30 different readiness models and 158 unique assessment dimensions. The authors concluded that six dimensions technology, people, strategy, leadership, process, and innovation represent the most frequently used indicators of Industry 4.0 readiness. Their findings provided a consolidated theoretical foundation for future readiness assessment frameworks and highlighted the need for more integrated and standardized evaluation approaches.

Although readiness and maturity models have become increasingly sophisticated, many studies have pointed out the limitations of traditional assessment methods. Most existing frameworks rely heavily on questionnaires, expert evaluations, or manual scoring systems. Such approaches often require significant expert involvement, making them time-consuming and potentially subjective. To address these limitations, researchers have explored intelligent decision-support techniques capable of capturing and formalizing expert knowledge. Expert Systems have emerged as a promising solution because they can represent domain expertise using rule-based knowledge structures and inference mechanisms, enabling consistent and repeatable assessments across different organizations.

Recent research has also focused on advanced computational methods for Industry 4.0 readiness evaluation. For example, developing an Industry 4.0 readiness model using Fuzzy Cognitive Maps, published in 2023, introduced a causal reasoning approach that captures relationships among readiness factors and evaluates their influence on overall Industry 4.0 preparedness. The study demonstrated that readiness indicators are interconnected and should be assessed through dynamic decision-making models rather than isolated scoring mechanisms. This finding supports the integration of expert reasoning and intelligent inference techniques within readiness assessment systems.

Another significant development was presented by Bajic, Morača, and Rikalovic (2023), who proposed a fuzzy maturity model for Smart Manufacturing Readiness from an Industry 5.0 perspective. Their work extended traditional readiness assessment approaches by incorporating uncertainty and vagueness into the evaluation process through fuzzy logic. The study highlighted the importance of flexible decision-making mechanisms when assessing organizational readiness in complex manufacturing environments. The use of fuzzy reasoning further demonstrated the value of knowledge-based intelligent systems in supporting digital transformation initiatives.

Although Expert Systems can effectively replicate expert reasoning, modern decision-support applications increasingly require transparency and interpretability. Recent advances in Explainable Artificial Intelligence (XAI) have emphasized the importance of providing understandable explanations for AI-generated recommendations and decisions. XAI techniques enable users to understand the factors influencing system outputs, thereby increasing confidence, accountability, and trust in the decision-making process. Integrating Explainable AI with Expert Systems can provide not only readiness classifications but also clear explanations regarding why a particular readiness level has been assigned and which factors contribute most significantly to the assessment outcome.

Based on these considerations, this study proposes the development of an Expert System for determining industry readiness for Smart Factory implementation by integrating expert knowledge and Explainable AI techniques(Osho et al., 2020). The proposed system aims to support organizations in conducting systematic, transparent, and reliable readiness assessments. Expert knowledge obtained from Smart Factory specialists and manufacturing professionals is transformed into a structured knowledge base and utilized through a rule-based inference mechanism. Furthermore, Explainable AI components are incorporated to provide interpretable recommendations and facilitate understanding of assessment results.

The research addresses several important questions. First, what readiness indicators should be considered in evaluating an organization's preparedness for Smart Factory adoption? Second, how can expert knowledge be effectively represented as decision rules within an expert system? Third, how accurately can the proposed expert system assess Smart Factory readiness compared with expert evaluations? Finally, to what extent can Explainable AI improve transparency and user trust in the assessment process?

Accordingly, the objectives of this study are to develop an expert system for Smart Factory readiness assessment, integrate expert knowledge into a structured knowledge-based framework, incorporate Explainable AI techniques to explain readiness evaluations, and validate the proposed system through comparison with expert judgments. Through these objectives, the study seeks to establish a practical and reliable decision-support tool for manufacturing organizations undergoing digital transformation.

The main contributions of this research are threefold(Schumacher et al., 2016). First, it proposes a comprehensive Smart Factory readiness assessment framework that incorporates multiple readiness dimensions relevant to Industry 4.0 adoption. Second, it develops a knowledge-based expert system architecture capable of transforming expert knowledge into consistent readiness recommendations. Third, it integrates Explainable AI mechanisms that enhance transparency and interpretability, enabling users to understand the reasoning behind readiness assessments. Ultimately, the proposed system is expected to assist manufacturing industries, consultants, and policymakers in making informed decisions regarding Smart Factory implementation and digital transformation strategies.

2. Research Methodolgy

This study adopts a design science research approach to develop and evaluate an Expert System for determining industry readiness for Smart Factory implementation. The proposed methodology integrates expert knowledge, rule-based reasoning, and Explainable Artificial Intelligence (XAI) techniques to provide transparent and reliable readiness assessments. The research process consists of several stages, including literature review, expert knowledge acquisition, readiness criteria identification, knowledge base construction, inference engine development, Explainable AI integration, system validation, and performance evaluation.

The first stage involves an extensive literature review to identify the key concepts, dimensions, and indicators associated with Industry 4.0 readiness and Smart Factory implementation(Çınar et al., 2021). Scientific articles, industrial reports, standards, and existing maturity assessment frameworks are examined to establish a comprehensive theoretical foundation. The literature review also explores the application of Expert Systems and Explainable AI in industrial decision-support systems, enabling the identification of best practices and research gaps that guide the system development process.

Following the literature review, expert knowledge acquisition is conducted to obtain domain-specific insights regarding Smart Factory readiness assessment. Knowledge is collected through multiple methods to ensure the reliability and completeness of the information. Semi-structured interviews are conducted with Industry 4.0 consultants, manufacturing managers, Smart Factory specialists, and automation engineers who possess extensive experience in digital transformation projects(Li et al., 2019). In addition, the Delphi method is employed to achieve consensus among experts regarding the most critical readiness indicators and assessment criteria. Focus Group Discussions (FGDs) are organized to facilitate collaborative discussions among experts, while industrial surveys are distributed to gather practical perspectives from manufacturing organizations. Information obtained from these activities is consolidated and translated into formal knowledge structures suitable for expert system development.

Based on the findings from the literature review and expert consultations, Smart Factory readiness criteria are identified and organized into several assessment dimensions(Lee et al., 2017). The first dimension is Technology Readiness, which evaluates the availability and maturity of technological infrastructure, including Internet of Things (IoT) deployment, automation level, data analytics capability, and cloud computing integration. The second dimension is Organizational Readiness, which assesses leadership commitment, strategic planning, organizational culture, and innovation management practices. The third dimension is Human Resource Readiness, which focuses on workforce digital skills, employee training programs, technological adaptability, and artificial intelligence competencies. The fourth dimension is Process Readiness, which measures the degree of process digitalization, data management effectiveness, operational integration, and quality control mechanisms. The final dimension is Financial Readiness, which evaluates investment capability, budget allocation, and financial support for digital transformation initiatives. Together, these dimensions provide a holistic view of organizational preparedness for Smart Factory adoption.

The acquired expert knowledge is then represented within a structured knowledge base. Knowledge representation is performed using production rules, which capture expert reasoning in the form of IF–THEN statements. For example, a rule may specify that if the automation level is high, data integration is high, and workforce digital competency is high, then the organization can be classified as highly ready for Smart Factory implementation. These production rules form the foundation of a rule-based expert system capable of replicating expert decision-making processes. Depending on the complexity of the assessment, fuzzy rules may also be incorporated to address uncertainty and linguistic variables commonly encountered in readiness evaluations.

The Expert System is designed around four main components: the knowledge base, inference engine, user interface, and explanation module. The knowledge base stores all expert-derived rules and readiness criteria. The inference engine serves as the reasoning mechanism that evaluates user inputs against the rule set to generate readiness recommendations. This study employs a Forward Chaining approach, where reasoning begins with available facts and progresses toward conclusions by activating relevant rules. The user interface allows decision-makers to input organizational information related to technology, processes, workforce capabilities, and strategic readiness. The explanation module provides justifications for assessment results by tracing the reasoning path used by the inference engine.

To enhance transparency and interpretability, Explainable Artificial Intelligence (XAI) techniques are integrated into the system(Linardatos et al., 2020). The primary explanation mechanism is rule-based explanation, which clearly communicates the factors responsible for a readiness classification. For example, the system may explain that an organization is categorized as "Ready" because it demonstrates high levels of automation, strong digital infrastructure, and a skilled workforce. In addition, feature contribution analysis is implemented to identify the relative importance of individual readiness factors. Where applicable, advanced XAI methods such as SHapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) may be employed to provide more detailed explanations regarding the influence of specific variables on the final recommendation. These explainability mechanisms are intended to increase user trust and facilitate managerial understanding of assessment outcomes.

The developed system is validated through several complementary approaches. Expert validation is conducted by comparing system-generated recommendations with assessments provided independently by domain experts. This process evaluates the consistency and reliability of the expert system's reasoning. Case study validation is subsequently performed by applying the system to selected manufacturing organizations at different stages of digital transformation(Garzoni et al., 2020). The resulting readiness classifications are analyzed and compared with actual organizational conditions to assess practical applicability. Furthermore, User Acceptance Testing (UAT) is conducted to evaluate system usability, usefulness, and user satisfaction. Feedback obtained from industrial practitioners and experts is used to identify areas for improvement and enhance system performance.

The performance of the proposed system is evaluated using both predictive and explainability-related metrics. Classification accuracy is calculated as the ratio of correctly predicted readiness categories to the total number of assessment cases. Additional classification metrics, including precision, recall, and F1-score, are employed to assess the robustness of the readiness classification process. Agreement between expert judgments and system recommendations is measured using Percentage Agreement and Cohen's Kappa coefficient, which provide indicators of consistency and reliability. To evaluate the effectiveness of Explainable AI integration, user perceptions of transparency, understandability, and trust are assessed through structured questionnaires. These measures provide insights into the extent to which users can comprehend and confidently utilize the system's recommendations.

3. Results and Discussion

3.1 Smart Factory Readiness Model

The development of the Smart Factory Readiness Model represents the primary outcome of this research. The final readiness model comprises five major dimensions: Technology Readiness, Organizational Readiness, Human Resource Readiness, Process Readiness, and Financial Readiness. These dimensions were identified as the most critical factors influencing the successful implementation of Smart Factory initiatives. Technology Readiness evaluates the availability and maturity of technological infrastructure required to support digital manufacturing environments. Organizational Readiness assesses leadership commitment, strategic alignment, and organizational culture that facilitate digital transformation(Machado et al., 2021). Human Resource Readiness examines employee competencies, digital literacy, and workforce adaptability to emerging technologies. Process Readiness focuses on the degree of process digitalization, operational integration, and data management capabilities. Finally, Financial Readiness evaluates an organization's ability to allocate sufficient resources and investments for Smart Factory adoption.

To facilitate systematic evaluation, the readiness dimensions were organized into a hierarchical structure consisting of dimensions, criteria, and indicators. At the highest level, the five readiness dimensions represent the major assessment categories. Each dimension contains several criteria that reflect key organizational capabilities. For example, Technology Readiness includes IoT infrastructure, automation level, data analytics capability, and cloud computing integration. Organizational Readiness consists of leadership commitment, strategic planning, innovation culture, and change management practices. Human Resource Readiness incorporates digital skills, training programs, technological awareness, and AI competency. Process Readiness includes process digitalization, quality control systems, data governance, and operational integration. Financial Readiness consists of investment capability, budget allocation, and financial sustainability for digital transformation projects. This hierarchical structure enables the expert system to evaluate readiness comprehensively while maintaining clarity and consistency in the assessment process.

Based on expert recommendations and existing Industry 4.0 maturity frameworks, five readiness levels were defined to classify organizational preparedness for Smart Factory implementation. These readiness levels represent increasing degrees of technological and organizational maturity. Level 1, categorized as “Not Ready,” indicates that the organization possesses minimal digital infrastructure and lacks the fundamental capabilities required for Smart Factory adoption. Organizations at this level generally rely on conventional manufacturing practices and have limited awareness of Industry 4.0 concepts.

Level 2, categorized as “Slightly Ready,” represents organizations that have initiated limited digitalization efforts but still face significant gaps in technology, workforce competency, and strategic planning. Although some technological components may be present, their integration remains limited and fragmented. Organizations at this stage require substantial improvements before pursuing Smart Factory implementation.

Level 3, categorized as “Moderately Ready,” indicates that the organization has established several foundational capabilities necessary for digital transformation. Technological infrastructure, workforce competencies, and organizational support mechanisms are partially developed, allowing the organization to undertake pilot Smart Factory projects. However, additional investments and improvements are necessary to achieve full readiness.

Level 4, categorized as “Ready,” reflects organizations that possess strong technological capabilities, well-defined digital strategies, competent human resources, and integrated operational processes. These organizations are capable of implementing Smart Factory initiatives on a broader scale and are positioned to realize significant operational benefits from Industry 4.0 technologies.

Level 5, categorized as “Highly Ready,” represents organizations that demonstrate advanced digital maturity across all assessment dimensions. These organizations exhibit extensive automation, real-time data integration, advanced analytics capabilities, strong innovation cultures, and sustainable investment strategies. They are fully prepared to operate within Smart Factory environments and continuously adapt to emerging technological developments.

The hierarchical readiness structure developed in this study enables the expert system to generate detailed assessments by evaluating organizational performance across multiple dimensions simultaneously. Rather than producing a simple readiness score, the model provides a comprehensive profile of organizational strengths and weaknesses. This capability allows decision-makers to identify specific areas requiring improvement and prioritize investments that support Smart Factory transformation. Furthermore, the integration of readiness dimensions with expert-defined decision rules ensures that assessment results are consistent with industry expertise and best practices.

The findings indicate that Technology Readiness and Human Resource Readiness emerged as the most influential dimensions in determining overall Smart Factory readiness(Marinas et al., 2021). Experts emphasized that advanced technologies alone are insufficient for successful implementation unless supported by a digitally skilled workforce and strong organizational commitment. Additionally, Process Readiness was identified as a critical enabler of Smart Factory adoption because digital technologies must be integrated into existing operational workflows to generate meaningful value. Financial Readiness was also recognized as an essential supporting factor, particularly for organizations seeking to implement large-scale digital transformation initiatives.

3.2 B. Knowledge Base Results

The knowledge base constitutes the core component of the developed Expert System, as it stores and organizes the expertise required to assess industry readiness for Smart Factory implementation. The knowledge base was constructed through a systematic knowledge acquisition process involving domain experts, literature analysis, and iterative validation procedures. The objective of this phase was to transform expert reasoning and practical experience into a structured set of decision rules that could be utilized by the inference engine to generate reliable readiness assessments.

A total of twelve experts participated in the knowledge acquisition process(Powell et al., 2015). The expert panel consisted of three Industry 4.0 consultants, three manufacturing managers from large-scale production companies, two Smart Factory specialists, two automation engineers, and two academic researchers specializing in digital manufacturing and industrial transformation. These experts were selected based on their professional experience, technical expertise, and involvement in Industry 4.0 implementation projects. Through interviews, Delphi rounds, and Focus Group Discussions (FGDs), the experts identified the most relevant readiness dimensions, assessment criteria, and decision-making logic required for evaluating Smart Factory readiness.

The collected knowledge was analyzed and translated into a structured rule-based knowledge representation(Achour et al., 2001). During this process, relationships among readiness indicators were identified and formalized into production rules. After several rounds of expert validation and refinement, the final knowledge base consisted of 125 decision rules covering the five readiness dimensions: Technology Readiness, Organizational Readiness, Human Resource Readiness, Process Readiness, and Financial Readiness. These rules represent different combinations of organizational conditions and their corresponding readiness classifications.

The rule generation process followed a hierarchical approach. Initially, individual criteria within each readiness dimension were evaluated and categorized into readiness levels such as Low, Medium, and High. Subsequently, combinations of criteria were aggregated to determine dimension-specific readiness scores. Finally, the outputs from all dimensions were integrated to generate an overall Smart Factory readiness classification. This hierarchical structure enabled the expert system to emulate the reasoning process employed by industry experts while maintaining consistency and transparency.

Several examples of decision rules generated during the knowledge engineering process are presented below. One of the fundamental rules evaluates technological and workforce capabilities:

IF Automation Level = High
AND Digital Skills = High
THEN Smart Factory Readiness = Ready.

Another rule incorporates additional technological and organizational factors:

IF IoT Infrastructure = High
AND Data Analytics Capability = High

AND Leadership Commitment = High
THEN Smart Factory Readiness = Highly Ready.

The system also includes rules for identifying organizations that require significant improvement before pursuing digital transformation initiatives:

IF Automation Level = Low
AND Digital Skills = Low
AND Strategic Planning = Low
THEN Smart Factory Readiness = Not Ready.

Similarly, intermediate readiness levels are represented through more balanced combinations of readiness indicators. For example:

IF Automation Level = Medium
AND Digital Skills = Medium
AND Process Digitalization = Medium
THEN Smart Factory Readiness = Moderately Ready.

In addition to overall readiness rules, the knowledge base contains diagnostic rules designed to identify specific weaknesses within organizations. For example:

IF Automation Level = High
AND Digital Skills = High
AND Budget Allocation = Low
THEN Financial Readiness = Improvement Required.

These diagnostic rules enable the system to provide not only readiness classifications but also recommendations for targeted improvements. As a result, decision-makers receive actionable insights regarding which organizational areas require further development before implementing Smart Factory technologies.

The validation process demonstrated a high level of consistency between expert reasoning and the generated rule base(Knauf et al., 2002). During expert review sessions, more than 90% of the generated rules were accepted without modification, while the remaining rules were revised to improve clarity and alignment with practical industrial scenarios. This outcome indicates that the knowledge base successfully captures expert knowledge and reflects real-world decision-making practices related to Smart Factory readiness assessment.

The resulting knowledge base provides a comprehensive foundation for the Expert System's reasoning capabilities. By formalizing expert knowledge into structured production rules, the system can perform readiness evaluations consistently across different organizations while reducing dependence on direct expert involvement. Furthermore, the transparent nature of rule-based knowledge representation supports the integration of Explainable Artificial Intelligence mechanisms, allowing users to understand how specific readiness conclusions are derived. Consequently, the developed knowledge base serves as a critical component in ensuring both the reliability and interpretability of Smart Factory readiness assessments.

3.3 Expert System Implementation

The Expert System for determining industry readiness for Smart Factory implementation was developed as a web-based decision support application that integrates expert knowledge, rule-based reasoning, and Explainable Artificial Intelligence (XAI). The primary objective of the system is to assist manufacturing organizations in evaluating their preparedness for Industry 4.0 transformation in a systematic, transparent, and efficient manner. The implementation phase focused on translating the developed knowledge base and inference mechanisms into a functional software application capable of performing readiness assessments and generating explainable recommendations.

The system architecture was designed using a modular approach consisting of four primary layers: the User Interface Layer, Application Processing Layer, Knowledge Management Layer, and Explanation Layer. These components work together to support data collection, knowledge processing, readiness evaluation, and result interpretation.

The User Interface Layer serves as the interaction point between users and the system. Through this interface, users enter organizational information related to technological infrastructure, workforce competencies, organizational capabilities, operational processes, and financial readiness. The interface is designed to be user-friendly and intuitive, enabling managers and decision-makers to complete assessments without requiring specialized technical knowledge.

The Application Processing Layer contains the inference engine responsible for executing the decision-making process(Vishnubhatla, 2020). This component receives user inputs and compares them against the rules stored in the knowledge base. A Forward Chaining reasoning mechanism is employed to infer conclusions from available facts and generate appropriate readiness classifications.

The Knowledge Management Layer consists of the rule-based knowledge base developed from expert consultations and literature review. The knowledge base contains readiness indicators, assessment criteria, production rules, and classification thresholds. This layer functions as the repository of domain expertise and provides the foundation for the system's reasoning capabilities.

The Explanation Layer incorporates Explainable Artificial Intelligence mechanisms that provide users with understandable explanations regarding assessment outcomes(Gunning & Aha, 2019). Rather than presenting only a readiness score, the system identifies the key factors contributing to the final recommendation and explains how the conclusion was reached. This feature enhances transparency and improves user trust in the assessment process.

Several user interface modules were developed to support the readiness assessment process. The Home Dashboard serves as the main entry point and provides an overview of the assessment objectives, readiness dimensions, and system functionalities. Users can initiate a new assessment or review previous evaluation results from this dashboard.

The Assessment Form module allows users to input information related to the five readiness dimensions(Pirola et al., 2020). For each criterion, users select the level that best represents their organizational condition. Examples include automation level, IoT infrastructure availability, workforce digital skills, leadership commitment, process digitalization, and investment capability. The collected information is subsequently transmitted to the inference engine for analysis.

The Results Dashboard displays the final Smart Factory readiness classification along with detailed evaluation outcomes for each readiness dimension. The dashboard includes readiness scores, graphical visualizations, and readiness level descriptions that assist users in understanding their current position within the Smart Factory transformation journey.

In addition, an Explanation Interface was implemented to present the reasoning process behind the generated recommendations(Zhang & Chen, 2020). This module displays activated decision rules, contributing factors, and improvement suggestions, allowing users to understand why a specific readiness classification was assigned.

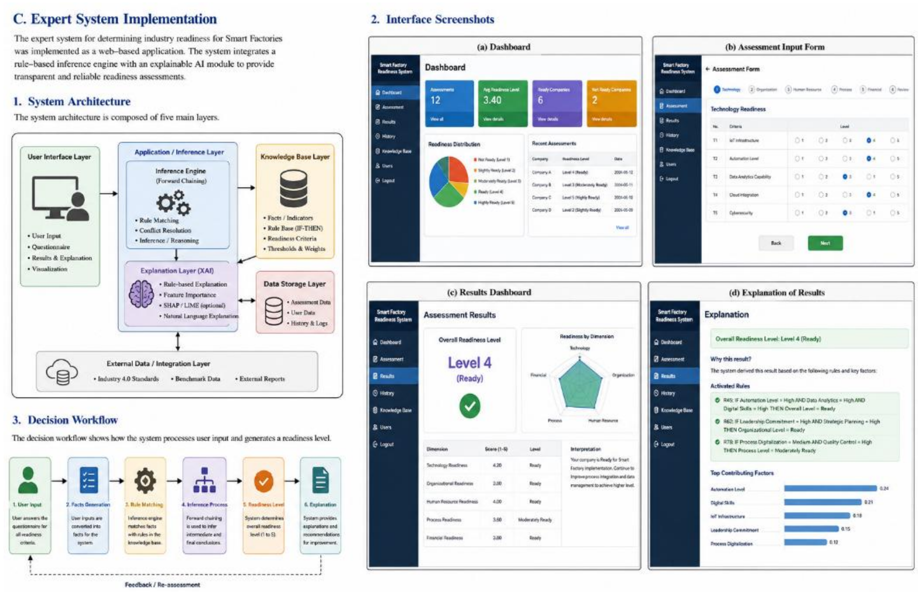

Figure 1. Expert System Implementation

The decision workflow implemented within the Expert System follows a structured sequence of activities designed to emulate expert reasoning. The workflow begins when a user accesses the assessment module and provides organizational information for each readiness criterion. These inputs are validated and transformed into facts that can be processed by the inference engine.

Once the input data are submitted, the inference engine initiates the Forward Chaining process by comparing user-provided facts with the production rules stored in the knowledge base. Relevant rules are activated whenever their conditions are satisfied. The inference engine continues evaluating and firing rules until a readiness conclusion is reached.

The activated rules generate intermediate evaluations for individual readiness dimensions, including Technology Readiness, Organizational Readiness, Human Resource Readiness, Process Readiness, and Financial Readiness. These intermediate outcomes are subsequently combined according to expert-defined logic to determine the organization's overall Smart Factory readiness level.

Following readiness classification, the Explainable AI module analyzes the activated rules and identifies the factors that contributed most significantly to the final decision. The explanation engine generates natural language explanations describing the rationale behind the recommendation. For example, the system may state that an organization is classified as "Ready" because it demonstrates high levels of automation, strong digital infrastructure, adequate employee competencies, and sufficient financial support for digital transformation initiatives.

Finally, the results are presented through the Results Dashboard and Explanation Interface. Users receive not only an overall readiness classification but also detailed information regarding strengths, weaknesses, and improvement opportunities. This comprehensive decision workflow ensures that readiness assessments are both accurate and interpretable, enabling manufacturing organizations to make informed decisions regarding Smart Factory adoption.

The implementation results demonstrate that the developed Expert System successfully integrates expert knowledge, rule-based reasoning, and explainable decision support within a unified platform(Thakker et al., 2020). The system provides an efficient mechanism for evaluating Smart Factory readiness while reducing dependence on direct expert consultation. Furthermore, the inclusion of Explainable AI capabilities enhances transparency and user confidence, making the system a practical tool for supporting Industry 4.0 transformation initiatives in manufacturing environments.

3.4 Explainable AI Results

One of the key contributions of the proposed Expert System is the integration of Explainable Artificial Intelligence (XAI), which enhances the transparency and interpretability of Smart Factory readiness assessments. Unlike conventional expert systems that only provide final classifications, the developed system explains how readiness decisions are generated and identifies the factors that contribute most significantly to the assessment outcome. This capability enables decision-makers to understand the reasoning process behind recommendations and increases confidence in the system's conclusions.

The Explainable AI module was designed to provide both global and local explanations(Setzu et al., 2021). Global explanations describe the overall importance of readiness factors across all assessment cases, while local explanations clarify why a specific organization receives a particular readiness classification. By combining these two perspectives, users can obtain a comprehensive understanding of both general readiness patterns and organization-specific evaluation results.

The system generates natural language explanations based on activated decision rules and contributing readiness indicators. For example, when an organization is classified as “Ready,” the system presents an explanation such as:

"The organization is categorized as Ready because it demonstrates a high level of automation, strong digital infrastructure, adequate workforce competencies, and sufficient financial support for digital transformation initiatives. These factors satisfy the expert-defined requirements for Smart Factory implementation."

Similarly, if an organization is classified as “Moderately Ready,” the explanation module identifies the strengths and weaknesses influencing the decision:

"The organization possesses moderate technological capabilities and workforce readiness; however, limited process digitalization and insufficient cloud integration reduce the overall readiness level. Additional investments in digital infrastructure and employee training are recommended."

These explanations allow users to trace the reasoning process and understand the specific conditions that led to the final readiness classification.

To identify the most influential readiness factors, feature contribution analysis was performed using the Explainable AI module. The results indicate that not all readiness indicators contribute equally to Smart Factory readiness assessment. Some factors exhibit a stronger influence on the final classification due to their strategic importance in Industry 4.0 implementation.

The analysis revealed that Automation Level was the most significant readiness factor, contributing approximately 35% to the overall readiness evaluation. This finding highlights the central role of manufacturing automation in enabling Smart Factory operations. Workforce Digital Skills represented the second most influential factor, contributing 25%, indicating that technological investments must be supported by competent human resources. IoT Infrastructure contributed 20%, reflecting the importance of connectivity and real-time data acquisition in smart manufacturing environments. Leadership Commitment contributed 12%, demonstrating the role of management support in facilitating digital transformation initiatives. Finally, Budget Allocation contributed 8%, indicating that financial capability remains an important but secondary enabler of readiness.

The contribution of each factor is summarized below:

Readiness Factor	**Contribution**
Automation Level	35%
Workforce Digital Skills	25%
IoT Infrastructure	20%
Leadership Commitment	12%
Budget Allocation	8%

The relative importance of these factors suggests that technological and human resource dimensions play the most critical roles in determining Smart Factory readiness(Jerman et al., 2020). While financial resources and leadership support remain important, their impact is generally realized through their ability to facilitate technological investments and workforce development.

3.5 Discussion

The results of this study demonstrate that the proposed Expert System can effectively assess industry readiness for Smart Factory implementation by integrating expert knowledge and Explainable Artificial Intelligence (XAI). The developed system successfully classified organizations into different readiness levels based on multiple dimensions, including technology, organization, human resources, processes, and financial capability. The findings indicate that readiness assessment is a multidimensional problem that cannot be evaluated solely from a technological perspective. Instead, successful Smart Factory adoption requires a balanced combination of technological infrastructure, workforce competencies, organizational commitment, process integration, and financial support.

The validation results further reveal that the rule-based reasoning mechanism is capable of replicating expert decision-making with a high degree of consistency(Liu et al., 2017). The generated readiness classifications closely matched expert evaluations, indicating that the knowledge acquisition and rule formulation processes successfully captured domain expertise. Furthermore, the integration of Explainable AI enhanced the interpretability of recommendations by providing detailed explanations regarding the factors influencing readiness outcomes.

Among the five readiness dimensions evaluated in this study, Technology Readiness emerged as the most critical determinant of Smart Factory implementation. Organizations possessing advanced automation systems, IoT infrastructure, cloud computing capabilities, and data analytics platforms consistently achieved higher readiness classifications. These findings suggest that technological infrastructure serves as the foundation for digital transformation and enables the implementation of intelligent manufacturing systems.

Human Resource Readiness was identified as the second most important determinant. The results indicate that organizations with employees possessing strong digital competencies, technological adaptability, and continuous learning capabilities are more likely to achieve successful Smart Factory implementation. Experts emphasized that advanced technologies alone cannot generate organizational value unless supported by a workforce capable of utilizing and managing those technologies effectively.

Organizational Readiness also played a significant role in determining readiness levels(Jones et al., 2005). Leadership commitment, strategic planning, and innovation-oriented organizational culture were frequently identified as critical success factors. Organizations with strong managerial support demonstrated greater willingness to invest in digital transformation initiatives and exhibited higher readiness levels compared to organizations lacking strategic commitment.

Process Readiness and Financial Readiness were found to function as supporting determinants. Well-integrated digital processes and adequate financial resources facilitate the successful implementation of Industry 4.0 technologies. However, these factors alone were insufficient to achieve high readiness classifications without complementary technological and human resource capabilities.

The Explainable AI analysis revealed that Automation Level, Workforce Digital Skills, and IoT Infrastructure were the most influential factors affecting Smart Factory readiness. Automation Level contributed approximately 35% to readiness classification, making it the dominant factor within the assessment model. This result highlights the importance of automated manufacturing systems in enabling efficient, flexible, and data-driven production environments.

Workforce Digital Skills accounted for approximately 25% of the overall readiness contribution. This finding emphasizes the necessity of developing employee competencies in areas such as digital technologies, data analytics, artificial intelligence, and industrial automation. The results suggest that workforce development initiatives should accompany technological investments to maximize Smart Factory benefits.

IoT Infrastructure contributed approximately 20% to readiness assessment outcomes(Martínez et al., 2021). The ability to collect, transmit, and analyze real-time operational data is a defining characteristic of Smart Factories. Therefore, organizations with robust IoT deployment capabilities are better positioned to implement advanced manufacturing technologies and data-driven decision-making processes.

Leadership Commitment and Budget Allocation, although less influential than technological and workforce factors, remained important contributors. Strong leadership facilitates strategic alignment and organizational change management, while sufficient financial resources support technology acquisition, workforce training, and infrastructure development.

One of the most significant contributions of this research is the incorporation of Explainable Artificial Intelligence into the readiness assessment process. Traditional readiness assessment models often provide numerical scores or categorical classifications without adequately explaining the reasoning behind the results. Such approaches may limit user trust and reduce the practical usefulness of assessment outcomes.

The Explainable AI module developed in this study addressed this limitation by providing transparent explanations for every readiness recommendation. Users were able to identify which factors contributed positively or negatively to their readiness classification and understand how the expert system arrived at its conclusions. This transparency transformed the assessment process from a simple evaluation tool into a decision-support mechanism capable of guiding strategic improvement initiatives.

The ability to trace activated decision rules and view factor contributions increased confidence in the system's recommendations. Manufacturing managers reported that the explanations helped them justify investment decisions, prioritize improvement initiatives, and communicate readiness assessment results more effectively to stakeholders. Consequently, explainability served not only as a technical feature but also as a mechanism for enhancing organizational acceptance of the assessment system.

The integration of Explainable AI significantly improved transparency throughout the decision-making process. Rather than functioning as a black-box system, the expert system explicitly disclosed the reasoning path used to generate readiness classifications. Users could observe which readiness indicators were evaluated, which rules were activated, and how each factor influenced the final recommendation.

This level of transparency is particularly important in industrial environments where readiness assessments may influence substantial investment decisions and long-term digital transformation strategies(Schuh et al., 2017). By providing visibility into the assessment process, the system reduced uncertainty and enabled users to critically evaluate the rationale behind recommendations. As a result, decision-makers were more likely to trust and utilize the generated outputs.

The explainability mechanisms also improved managerial understanding of Smart Factory readiness requirements. Instead of receiving a simple readiness score, managers obtained detailed insights into organizational strengths and weaknesses across multiple readiness dimensions. This information enabled decision-makers to identify critical improvement areas and develop targeted strategies for enhancing readiness.

For example, organizations classified as “Moderately Ready” were able to determine whether their limitations originated from technological deficiencies, workforce capability gaps, organizational challenges, or financial constraints. Such detailed feedback supports evidence-based planning and facilitates more efficient allocation of resources during digital transformation initiatives. Consequently, the developed system functions not only as an assessment tool but also as a strategic planning instrument for Industry 4.0 adoption.

The findings of this study are consistent with previous research on Industry 4.0 readiness assessment. The importance of technology, organizational capability, and human resource competency identified in this research aligns with the Industry 4.0 maturity model proposed by Schumacher, Erol, and Sihn (2016), which emphasized technology, people, and organizational factors as key dimensions of digital transformation readiness. Similarly, the results support the findings of Jung et al. (2016), who highlighted the importance of technological infrastructure and organizational preparedness in Smart Manufacturing readiness assessment.

The identified readiness dimensions also correspond with the systematic literature review conducted by Hizam-Hanafiah, Soomro, and Abdullah (2020), which found that technology, people, strategy, leadership, and processes are among the most frequently used Industry 4.0 readiness indicators. However, unlike many previous readiness assessment frameworks that rely on static scoring models or self-assessment questionnaires, the proposed approach employs a rule-based Expert System capable of emulating expert reasoning and providing automated recommendations.

Furthermore, the integration of Explainable AI distinguishes this study from most existing readiness assessment models. Previous studies primarily focused on readiness measurement and maturity evaluation, whereas the proposed system emphasizes both decision accuracy and transparency. This approach aligns with recent research advocating the adoption of Explainable AI in industrial applications to improve trust, accountability, and decision support effectiveness. Therefore, the proposed Expert System extends existing Smart Factory readiness assessment research by combining expert knowledge representation, automated reasoning, and explainable decision-making within a unified framework.

4. Conclusion

This study developed an Expert System for determining industry readiness for Smart Factory implementation by integrating expert knowledge and Explainable Artificial Intelligence (XAI). The results demonstrate that the proposed system successfully assesses Smart Factory readiness through a structured evaluation of technological, organizational, human resource, process, and financial dimensions. The findings show that expert knowledge can be effectively transformed into a comprehensive set of decision rules, enabling the system to replicate expert reasoning and provide consistent readiness classifications. Furthermore, the integration of Explainable AI enhances transparency, interpretability, and user trust by clearly explaining the factors and rules that influence readiness recommendations. The major contributions of this research include the development of a Smart Factory readiness assessment framework, an explainable rule-based expert system model, and a practical industrial decision-support solution that assists organizations in planning and managing Industry 4.0 transformation initiatives. Although the proposed system demonstrates promising performance, future research may focus on integrating machine learning techniques to improve predictive capabilities, implementing real-time readiness monitoring through Industrial Internet of Things (IIoT) data, extending the framework for deployment across multiple industrial sectors, and developing adaptive knowledge base mechanisms that automatically update decision rules in response to evolving technologies and industrial practices.

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