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An Integrated Analytic Hierarchy Process–Fuzzy Inference System Framework for Assessing Industry 4.0 Digital Maturity in Manufacturing Organizations

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Abstract: The fourth industrial revolution, or Industry 4.0, is fundamentally transforming manufacturing through the integration of cyber-physical systems, the Internet of Things (IoT), big data analytics, artificial intelligence, and intelligent automation. Despite its potential benefits, digital transformation remains challenging because it requires substantial investment, workforce capability development, and organizational change. Existing Industry 4.0 maturity models inadequately address systematic criteria weighting and uncertainty in digital maturity assessment, limiting their ability to provide comprehensive and decision-oriented evaluations. This study develops a seven-dimensional Industry 4.0 digital maturity framework by integrating the Analytic Hierarchy Process (AHP) and the Fuzzy Inference System (FIS). AHP is employed to derive expert-based priority weights among maturity dimensions, while FIS accommodates uncertainty and subjectivity in qualitative assessments through fuzzy reasoning. The research methodology comprises model conceptualization, criteria weighting using AHP, maturity evaluation using FIS, and validation through a case study of an automotive manufacturing company. The findings indicate that the Strategy, Culture and Expertise, and Organization and Change Management dimensions receive the highest priority weights, while Intelligent Manufacturing achieves the highest maturity score. The case organization obtained an overall maturity index of 0.73, corresponding to Stage 4, which indicates a high level of digitalization. The proposed AHP–FIS framework provides a structured, adaptive, and data-driven approach for evaluating Industry 4.0 maturity and offers decision support for prioritizing digital transformation initiatives and planning continuous improvement. The findings demonstrate the practical feasibility of the framework within the investigated automotive manufacturing context and provide methodological insights for future development of Industry 4.0 maturity assessment models.

Keywords: Industry 4.0; Digital maturity; Analytic Hierarchy Process; Fuzzy Inference System; Digital transformation

1 Introduction

The industrial revolution has entered its fourth phase, known as Industry 4.0, a fundamental transformation that integrates cyber-physical systems, the Internet of Things (IoT), artificial intelligence, big data analytics, and intelligent automation into manufacturing processes. This change is oriented not only toward technological digitization but also toward the restructuring of business models, decision-making patterns, and real-time value chain integration. Industry 4.0 enables manufacturing organizations to optimize production processes, increase productivity, and create systems that are adaptive and responsive to market dynamics. Through the utilization of big data and interconnected automated systems, companies can analyze large amounts of information in real time, reducing downtime, improving operational efficiency, and minimizing production errors [1].

While the benefits of Industry 4.0 have been widely recognized, its implementation is not a simple process. Digital transformation requires significant investment in technological infrastructure, workforce competency development, and organizational culture change. Many companies face challenges in determining their position on this transformation journey. Unpreparedness to adopt new technologies can lead to wasted investment, internal resistance, and the failure of digital system implementation. In a global context, the digital divide between companies and countries is increasingly evident, making the evaluation of readiness and maturity levels a pressing strategic issue.

Conceptually, a common approach to measuring an organization's readiness to adopt Industry 4.0 is through a readiness model. This model typically evaluates dimensions such as technological capabilities, IT infrastructure, organizational culture, and workforce skills [2]. However, a readiness model essentially only provides a snapshot of the initial state or level of readiness before the transformation begins. This model is less capable of evaluating the organization's ongoing development after implementation begins. In other words, a readiness model does not fully answer the question of how far an organization has developed and evolved in its digital transformation journey [3, 4].

As an alternative, maturity models offer a more comprehensive approach. Maturity models are designed to evaluate an organization's development stage by stage, from the early stages of digitalization to the full integration of Industry 4.0 principles [5]. Maturity models not only assess current conditions but also provide a strategic roadmap for continuous improvement. With a systematic evaluation framework, these models help organizations understand their relative position and formulate long-term development strategies [6]. However, the various maturity models that have been developed still face several methodological limitations.

First, most maturity models use a linear, score-based assessment approach that tends to be rigid and unable to capture the complexity and uncertainty of the evaluation process. Second, determining criteria weights is often subjective and not systematically structured. Third, processing ambiguous qualitative data still presents challenges in measuring difficult-to-quantify variables, such as organizational culture or the level of digital integration.

Furthermore, existing Industry 4.0 maturity models differ substantially in terms of evaluation dimensions, weighting mechanisms, uncertainty treatment, and validation procedures. Many models rely on equal or subjective weighting schemes, apply deterministic scoring approaches that inadequately capture qualitative ambiguity, and provide limited guidance for linking maturity assessment results to transformation planning and managerial action. Consequently, although maturity assessment has become increasingly important, current approaches still provide insufficient support for evidence-based decision-making and the prioritization of digital transformation initiatives in manufacturing organizations.

From an engineering management perspective, manufacturing organizations require maturity assessments not merely to identify their current digital position but also to prioritize investments, sequence implementation initiatives, allocate resources effectively, and guide capability development over time. Therefore, an effective maturity model should function not only as an assessment instrument but also as a decision-support mechanism that assists managers in formulating strategic transformation pathways and continuous improvement programs.

To address these challenges, this study proposes the development of an Industry 4.0 maturity model that integrates the Analytic Hierarchy Process (AHP) and the Fuzzy Inference System (FIS). AHP is an effective multi-criteria decision-making method for constructing a hierarchical structure of criteria and determining priority weights based on systematic pairwise comparisons. With this approach, the complexity of evaluation dimensions can be managed in a structured and quantitative manner [4].

In addition, the FIS is used to address uncertainty and subjectivity in the assessment process. Fuzzy logic allows for the representation of linguistic variables and qualitative evaluations in a more flexible form than conventional numerical approaches. The integration of AHP and FIS is expected to produce a more accurate, adaptive, and comprehensive evaluation model for measuring Industry 4.0 maturity levels [3].

Accordingly, this study contributes to the literature in three principal ways. First, it proposes a seven-dimensional Industry 4.0 maturity architecture specifically designed to capture the multidimensional nature of manufacturing digital transformation. Second, it integrates expert-derived AHP weighting and FIS-based reasoning to systematically incorporate both priority structures and qualitative uncertainty into maturity evaluation. Third, the proposed framework extends beyond assessment by linking maturity evaluation outcomes with transformation priorities and managerial actions, thereby providing a decision-oriented approach to planning and monitoring Industry 4.0 implementation.

Based on this background, the objectives of this study are: (1) developing a multidimensional and systematic Industry 4.0 maturity model framework; (2) determining the priority weight of each dimension and indicator using the AHP method; (3) designing an FIS-based evaluation system to manage uncertainty in assessment; and (4) producing an Industry 4.0 maturity index that can be used as a strategic tool for manufacturing organizations in planning sustainable digital transformation. Thus, this research is expected to provide theoretical contributions in the development of Industry 4.0 maturity assessment methodology, as well as practical contributions in the form of evaluation tools that can help organizations improve their digital capabilities systematically and in a targeted manner.

2 Analytic Hierarchy Process

2.1 Industry 4.0 Digital Transformation and Maturity Assessment

Industry 4.0 represents the latest phase of the industrial revolution, characterized by the integration of cyber-physical systems, the IoT, big data analytics, artificial intelligence, and intelligent automation in manufacturing processes. This transformation aims to create more efficient, flexible, adaptive, and real-time connected production systems. In the manufacturing context, digitalization impacts not only technological aspects but also organizational structures, business models, and strategic decision-making patterns [7].

The implementation of Industry 4.0 encourages companies to develop autonomous and data-driven production systems, enabling continuous process optimization. However, the digital transformation process often faces various challenges, such as limited technological infrastructure, a lack of digital competency in the workforce, and organizational cultural resistance to change. Therefore, companies require a systematic evaluation approach to understand their position on the digital transformation journey. This evaluation forms the basis for designing a targeted and sustainable implementation strategy, while minimizing the risk of technology investment failure. Therefore, measuring digital maturity is a critical component of the successful adoption of Industry 4.0 in the manufacturing sector.

Digital maturity models have emerged as strategic instruments for assessing an organization's level of development in adopting digital technologies. Unlike readiness models, maturity models emphasize the evaluation of continuous progress and stages of organizational evolution. These models typically encompass multiple dimensions, such as technology, strategy, leadership, organizational culture, and human resource capabilities [8].

In the context of Industry 4.0, maturity models help organizations identify their position on a specific developmental scale, from the early stages of digitalization to the full integration of intelligent systems. Furthermore, these models provide a roadmap for improvement that allows companies to systematically benchmark against industry best practices [9].

However, numerous studies indicate that many maturity models remain descriptive in nature and do not fully integrate robust quantitative methods into the evaluation process. The weighting of dimensions is often not based on a systematic multi-criteria approach, potentially introducing bias into the assessment results. These limitations open up space for the development of a maturity model that is more comprehensive, structured, and adaptive to the complexities of digital transformation in the manufacturing sector.

2.2 Application of the Analytic Hierarchy Process in Digital Assessment

The AHP is a multi-criteria decision-making method developed to address complex problems through a hierarchical structure. This method allows decision-makers to perform pairwise comparisons between criteria to determine priority weights based on their relative importance.

In the context of digital maturity evaluation, AHP is widely used to systematically structure dimensions and indicators. Its ability to integrate expert judgment makes AHP an effective tool for determining strategic priorities [10, 11]. The application of AHP in Industry 4.0 research has shown that this method is capable of producing quantitative metrics that align with organizational needs and priorities [12, 13]. However, AHP has limitations in handling uncertainty and ambiguity in qualitative assessments. The resulting numerical values often do not fully reflect the complexity of subjective variables, such as organizational culture or readiness for change. Therefore, complementary methods are needed that can accommodate this uncertainty more flexibly.

Moreover, an FIS is based on fuzzy set theory, which was introduced by Zadeh in 1965 [14]. FIS is designed to address uncertainty and subjectivity in decision-making processes by converting linguistic variables into numerical representations. In evaluating Industry 4.0 maturity, FIS is capable of modeling complex relationships between variables and transforming qualitative assessments into more flexible quantitative outputs [14]. This approach is particularly relevant in the context of digital transformation, where many indicators are difficult to measure precisely.

The integration of AHP and FIS results in a hybrid approach that combines the advantages of AHP's structured weighting with FIS's flexibility in handling uncertainty [15]. In the manufacturing sector, this hybrid model has proven effective in evaluating innovation, technology adoption, and organizational culture transformation [16]. Therefore, the AHP–FIS combination provides a strong methodological foundation for developing a comprehensive and adaptive manufacturing digital maturity model.

2.3 Critical Comparison and Research Gaps

Table 1 presents a comparison of representative Industry 4.0 maturity models that have been developed in previous studies.

The comparison of previous studies indicates that Industry 4.0 maturity models differ substantially regarding the number of maturity dimensions, weighting mechanisms, uncertainty treatment, validation procedures, and managerial applicability. Most existing models employ deterministic scoring approaches and equal or subjective weighting schemes that may inadequately reflect the relative importance of maturity dimensions in manufacturing environments. Furthermore, qualitative and ambiguous variables, such as organizational culture, digital competencies, and change readiness, remain difficult to assess accurately using conventional numerical approaches.

Another limitation concerns the practical use of maturity assessment outcomes. Most existing studies primarily focus on measuring maturity levels and classifying organizations into predefined stages. Comparatively less attention has been devoted to linking maturity assessment results with managerial decision-making, transformation priorities, resource allocation, and capability development pathways. Consequently, maturity assessment frequently becomes an end in itself rather than a strategic mechanism for guiding digital transformation initiatives.

Table 1. Comparative analysis of existing Industry 4.0 maturity models and their methodological characteristics

Ref.	Dimensions	Weighting Approach	Uncertainty Handling	Validation	Main Limitations
[17]	9 dimensions	Equal weighting	No	Case study	Static assessment and deterministic scoring
[18]	Manufacturing SME focus	Expert judgment	No	SME application	Limited consideration of qualitative uncertainty
[19]	Operations and supply chain focus	Expert-based	Fuzzy rules	Supply chain case	Limited multidimensional coverage
[8]	Smart manufacturing dimensions	Descriptive scoring	Partial	Single case study	Limited decision support capability
[3]	Industry 4.0 dimensions	AHP-based weighting	Partial fuzzy treatment	Single case	Absence of transformation roadmap
[15]	SME transformation dimensions	AHP and FIS integration	Yes	SME application	Limited manufacturing validation
This study	Seven-dimensional manufacturing architecture	Expert-derived AHP weighting	Full FIS reasoning	Automotive manufacturing case	Requires further multi-case validation

Note: SME = small and medium-sized enterprise; AHP = Analytic Hierarchy Process; FIS = Fuzzy Inference System.

From a systems perspective, Industry 4.0 maturity should not be interpreted as a collection of independent dimensions. Digital transformation develops through interdependent organizational capabilities in which strategic orientation, organizational culture, and change management frequently function as enabling factors for technology deployment, innovation capability, and intelligent manufacturing implementation. Weaknesses in one dimension may constrain progress in other dimensions and create bottlenecks that impede the overall transformation process. Therefore, assessing Industry 4.0 maturity requires an integrated framework capable of capturing both the multidimensional and interdependent nature of digital transformation.

Based on these gaps, this study proposes a seven-dimensional Industry 4.0 maturity framework that integrates the AHP and the FIS. The proposed framework seeks to address three methodological limitations identified in previous studies: (1) the lack of systematic weighting mechanisms for maturity dimensions, (2) the limited capability to manage uncertainty and qualitative ambiguity in maturity assessment, and (3) the insufficient linkage between maturity evaluation and managerial decision-making for planning digital transformation initiatives.

3 Methods

3.1 Research Design and Framework

This study adopts a model development and validation approach that integrates qualitative expert judgment and quantitative multi-criteria assessment techniques (Figure 1). The research process consists of eight sequential stages: (1) literature extraction and conceptualization, (2) questionnaire development, (3) expert selection, (4) development of the maturity architecture, (5) AHP-based criteria weighting, (6) FIS development and rule construction, (7) case study validation, and (8) sensitivity analysis.

3.2 Questionnaire Development

The questionnaire items were developed through a multi-stage procedure. First, relevant dimensions and indicators were extracted from previous studies on Industry 4.0 readiness and maturity assessment [5, 8, 17]. Second, an initial pool of measurement items was generated to represent each maturity dimension. Third, the preliminary instrument was reviewed by experts in manufacturing digital transformation to assess content relevance, clarity, and completeness. Fourth, pilot testing was conducted with a small group of manufacturing practitioners to identify ambiguous wording and improve item readability. Finally, revisions were incorporated to produce the final questionnaire instrument used in this study (Table 2). Each dimension was operationalized through four to six measurement items using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.3 Expert Selection and Respondent Profile

A purposive sampling approach was employed to select respondents with relevant expertise in manufacturing digital transformation. The study involved 138 middle- and senior-level managers from manufacturing companies in Indonesia. Eligibility criteria required respondents to have managerial responsibilities and practical experience in digital transformation initiatives, technology implementation projects, or Industry 4.0-related programs. To be included in the study, respondents were required to satisfy at least three criteria: (1) occupying a middle- or senior-level managerial position, (2) possessing a minimum of three years of experience in manufacturing operations or digital transformation initiatives, and (3) having direct involvement in technology implementation, process improvement, or Industry 4.0-related projects. Prior to completing the assessment, respondents attended a briefing session and written instructions regarding the study objectives, maturity dimensions, and pairwise comparison procedures to ensure a common understanding of the evaluation criteria.

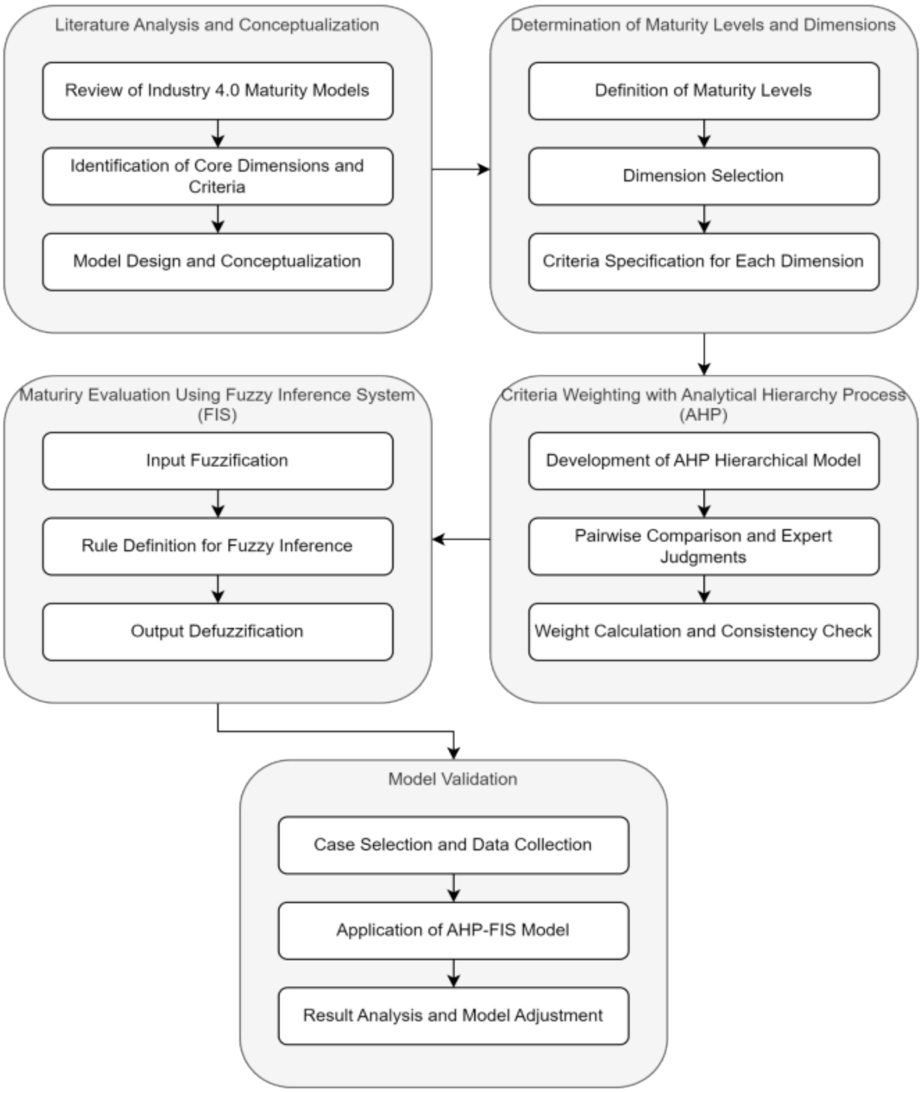

Figure 1. Research framework

Table 2. Dimensions and measurement items

Dimension	Number of Items	Main References
Strategy	5	[5, 17]
IT and Process Digitalization	6	[8, 14]
Customers	4	[18]
Culture and Expertise	5	[2]
Organization and Change Management	5	[6]
Innovation	4	[9]
Intelligent Manufacturing	5	[3]

Note: IT = Information Technology.

A total of 138 respondents participated in this study, comprising 92 middle-level managers (66.7%) and 46 senior-level managers (33.3%) from manufacturing companies in Indonesia (Table 3). The respondents represented various industrial sectors, including automotive (42.0%), electronics (29.7%), and food manufacturing (28.3%).

Most respondents possessed more than five years of professional experience (73.9%) and had been directly involved in digital transformation projects (81.9%). This profile indicates that the respondents had sufficient managerial experience and practical exposure to Industry 4.0 implementation, thereby enhancing the reliability and relevance of the pairwise comparisons and maturity assessments.

Table 3. Characteristics of the respondents (n = 138)

Characteristics		Frequency (n)	Percentage (%)
Managerial position	Middle Managers	92	66.7
	Senior Managers	46	33.3
Industrial sector	Automotive Sector	58	42.0
	Electronics Sector	41	29.7
	Food Manufacturing	39	28.3
Professional experience	$\leq$5 years of experience	36	26.1
	$>$5 years of experience	102	73.9
Digital transformation experience	Participated in digital transformation projects	113	81.9
	No direct participation	25	18.1

3.4 Development of the Industry 4.0 Maturity Framework

The initial stage involved a literature review and conceptual analysis of various existing Industry 4.0 maturity and readiness models. The goal was to identify key dimensions and criteria relevant to measuring the digital transformation of the manufacturing sector. Based on this synthesis, five maturity levels were established, ranging from Novice to Expert, representing incremental improvements in digital technology integration and organizational capabilities. The proposed maturity framework comprises seven dimensions: Strategy (D1), Information Technology (IT) and Process Digitalization (D2), Customers (D3), Culture and Expertise (D4), Organization and Change Management (D5), Innovation (D6), and Intelligent Manufacturing (D7). Each dimension was broken down into specific sub-dimensions to ensure a comprehensive evaluation.

Based on the literature synthesis and expert consultation process, a seven-dimensional maturity architecture was developed comprising Strategy, IT and Process Digitalization, Customers, Culture and Expertise, Organization and Change Management, Innovation, and Intelligent Manufacturing. These dimensions were further decomposed into measurable indicators to ensure comprehensive assessment coverage and to capture the multidimensional and interdependent nature of Industry 4.0 transformation. In this architecture, strategic orientation, organizational culture, and change management act as enabling capabilities that support technological deployment, innovation development, and intelligent manufacturing implementation.

3.5 Analytic Hierarchy Process Weighting and Pairwise Comparison Procedure

The AHP procedure followed the standard pairwise comparison approach proposed by Saaty. Respondents evaluated the relative importance of each maturity dimension using a nine-point comparison scale. Individual comparison matrices were aggregated to obtain collective judgments.

To improve assessment reliability, respondents received briefing sessions and written instructions regarding the meaning of each maturity dimension and the pairwise comparison procedure. Consistency testing was performed by calculating the Consistency Index (CI) and Consistency Ratio (CR). Following Saaty's recommendation, matrices with CR values below 0.10 were considered acceptable and logically consistent. When inconsistencies exceeded the threshold, respondents were requested to review and revise their evaluations.

3.6 Fuzzy Inference System Development

The FIS was developed through four sequential stages. First, an initial rule base was constructed using the weighted dimensions derived from the AHP analysis and the theoretical relationships identified in the literature. Second, the preliminary rules were reviewed by experts in manufacturing digital transformation and Industry 4.0 implementation. Third, inconsistencies and conflicting rules were discussed and refined through iterative consultation sessions. Finally, a consensus-based rule base consisting of 72 IF–THEN rules was established.

Input variables were represented by five linguistic categories: Very Low, Low, Medium, High, and Very High. The output variable represented five maturity stages ranging from Stage 1 (Novice) to Stage 5 (Expert). Triangular and trapezoidal membership functions were employed to capture uncertainty and ambiguity in qualitative assessments. Defuzzification was conducted using the centroid method to generate a continuous maturity score.

3.7 Maturity Level Definition and Validation Procedure

The maturity intervals were defined by dividing the normalized maturity scale (0–1) into five equal intervals representing progressive stages of digital transformation capability development (Table 4). This classification facilitates consistent interpretation of maturity scores and comparison across organizations.

Table 4. Definition of maturity stages

Stage	Maturity Index	Interpretation
Stage 1	0.00–0.20	Novice
Stage 2	0.21–0.40	Developing
Stage 3	0.41–0.60	Intermediate
Stage 4	0.61–0.80	Advanced
Stage 5	0.81–1.00	Expert

3.8 Sensitivity Analysis

To assess the robustness of the proposed framework, sensitivity analysis was performed by varying the AHP-derived weights by ±10%. The resulting maturity indices were recalculated to examine whether reasonable changes in weighting assumptions altered the maturity classification. This procedure provides additional evidence regarding the stability and practical reliability of the proposed AHP–FIS framework.

4 Results

4.1 Analytic Hierarchy Process-Based Weighting Results

The priority weights of the seven Industry 4.0 maturity dimensions were determined using the AHP. Pairwise comparisons among dimensions generated the comparison matrix presented in Table 5. The resulting weights indicate the relative importance of each dimension in contributing to overall manufacturing digital maturity. The seven dimensions evaluated in this study comprise Strategy (D1), IT and Process Digitalization (D2), Customers (D3), Culture and Expertise (D4), Organization and Change Management (D5), Innovation (D6), and Intelligent Manufacturing (D7). The coding system (D1–D7) is used throughout the analysis to facilitate the presentation of the AHP matrices and fuzzy inference procedures.

Table 5. Analytic Hierarchy Process (AHP) pairwise comparison matrix

Item	D1	D2	D3	D4	D5	D6	D7	Criteria Weights
D1	1.000	1.382	1.452	0.870	0.922	1.656	1.361	0.168
D2	0.724	1.000	1.168	0.694	0.809	1.357	1.001	0.131
D3	0.689	0.856	1.000	0.723	0.960	1.479	1.054	0.136
D4	1.149	1.441	1.383	1.000	1.502	1.930	1.575	0.164
D5	1.084	1.236	1.042	0.666	1.000	1.711	1.307	0.159
D6	0.604	0.737	0.676	0.518	0.584	1.000	0.688	0.134
D7	0.735	0.999	0.949	0.635	0.765	1.453	1.000	0.107

The AHP analysis (Table 5) revealed heterogeneous importance among the seven maturity dimensions. Strategy (D1 = 0.168), Culture and Expertise (D4 = 0.164), and Organization and Change Management (D5 = 0.159) received the highest priority weights. These findings suggest that organizational and managerial capabilities are perceived as the primary enablers of Industry 4.0 transformation. In particular, strategic orientation provides direction for digital initiatives, while organizational culture and change management facilitate technology adoption and capability development. Conversely, Intelligent Manufacturing (D7 = 0.107) obtained the lowest weight, indicating that advanced manufacturing technologies are generally viewed as outcomes of digital transformation rather than its initial drivers.

To evaluate the reliability of expert judgments, a consistency assessment was performed using the normalized comparison matrix presented in Table 6 and the Random CI values shown in Table 7.

The consistency assessment produced a CI of 0.0375 and a CR of 0.0284. The CR was substantially below the acceptable threshold of 0.10. These findings indicate that the collective judgments of the experts were logically consistent and suitable for deriving the final criteria weights. The low CR value demonstrates a high degree of agreement among respondents regarding the relative importance of the maturity dimensions and confirms the reliability of the weighting procedure.

Thus, AHP-based weighting provides clear prioritization of key dimensions in the maturity model. The results indicate that Industry 4.0 maturity extends beyond technological deployment and is strongly influenced by strategic, cultural, and organizational capabilities. The derived weights subsequently serve as inputs to the FIS, enabling the maturity evaluation process to incorporate both the relative importance of dimensions and the uncertainty inherent in qualitative assessments.

Table 6. Consistency checking

Item	D1	D2	D3	D4	D5	D6	D7	Criteria Weights
D1	0.166	0.185	0.200	0.165	0.133	0.156	0.170	0.168
D2	0.120	0.134	0.161	0.131	0.117	0.128	0.125	0.131
D3	0.114	0.154	0.138	0.137	0.139	0.140	0.132	0.136
D4	0.180	0.081	0.101	0.189	0.217	0.182	0.197	0.164
D5	0.142	0.193	0.170	0.139	0.145	0.162	0.164	0.159
D6	0.166	0.185	0.143	0.128	0.137	0.094	0.086	0.134
D7	0.111	0.069	0.087	0.111	0.111	0.137	0.125	0.107

Table 7. Random index

Size of Matrix	1	2	3	4	5	6	7
Random index	0	0	0.58	0.90	1.12	1.24	1.32

4.2 Organizational Maturity Assessment Results

To evaluate the applicability of the proposed framework, a case study was conducted in an automotive parts manufacturing company. Data were collected through a questionnaire consisting of 4–6 items for each maturity dimension using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire assessed the seven dimensions of the proposed maturity model, namely Strategy, IT and Process Digitalization, Customers, Culture and Expertise, Organization and Change Management, Innovation, and Intelligent Manufacturing.

The collected responses were normalized to satisfy the input requirements of the FIS. Five linguistic terms were defined for the input variables, namely Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). Similarly, the output variable was represented by five maturity stages ranging from Stage 1 (Novice) to Stage 5 (Expert). The set of 72 expert-validated fuzzy rules is provided in Appendix A.

A total of 72 fuzzy rules were developed based on the weighted criteria derived from the AHP analysis and subsequently refined through expert validation. The rules mapped combinations of the seven input dimensions into corresponding maturity stages and enabled the model to capture complex and uncertain relationships among organizational capabilities. The fuzzy inference process generated an overall company maturity index of 0.73.

The input membership function (Figure 2) illustrates the conversion of standardized scores into linguistic categories. This fuzzification process enables qualitative assessments and subjective judgments to be represented mathematically and integrated into the fuzzy reasoning mechanism.

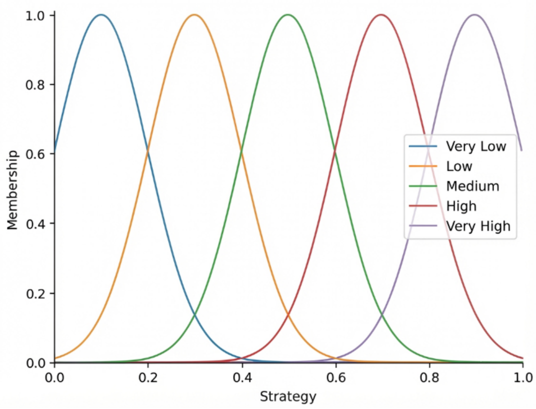

Figure 2. Input membership function

The output membership function shown in Figure 3 transforms the aggregated fuzzy reasoning results into a continuous maturity index. Based on this function, the resulting maturity index of 0.73 places the company within Stage 4, representing an advanced level of digital maturity.

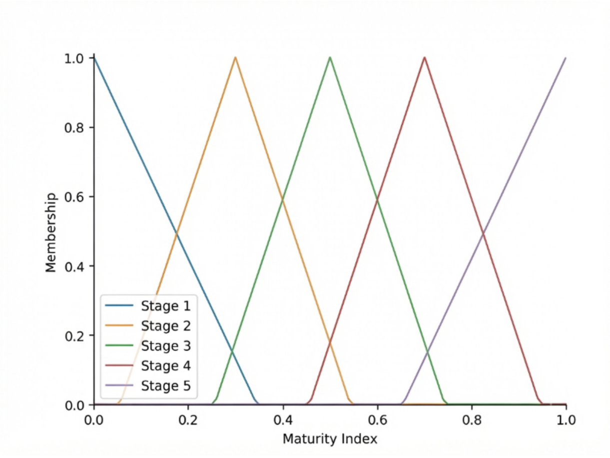

Figure 3. Output membership function

The maturity index of 0.73 indicates that the organization has progressed beyond the intermediate stages of digital transformation and has established substantial digital capabilities across its operational and managerial processes (Figure 4).

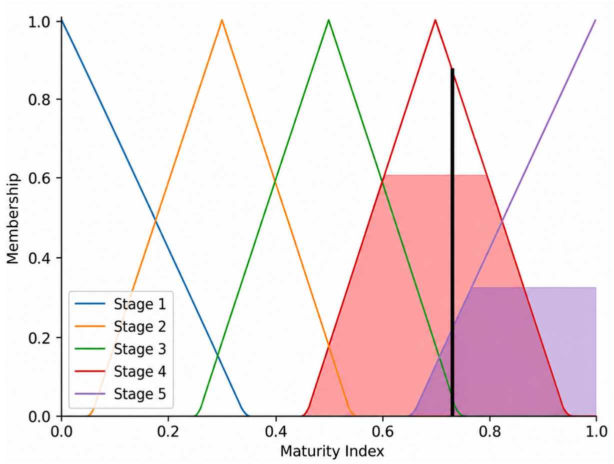

Figure 4. Output maturity index

The maturity-stage representation further confirms that the company has reached an advanced stage of Industry 4.0 implementation, characterized by the integration of digital technologies, structured innovation practices, and increasing organizational readiness for intelligent manufacturing initiatives (Figure 5).

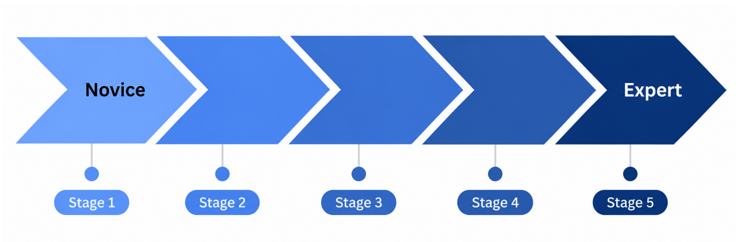

Figure 5. Level of maturity

Figure 6 presents the maturity scores across the seven dimensions of the proposed Industry 4.0 framework. The organization demonstrated relatively balanced digital capability development, with scores ranging from 0.75 to 1.00.

Intelligent Manufacturing achieved the highest score (1.00), followed by Strategy (0.90). The remaining dimensions attained scores of approximately 0.75, indicating that the company has established a strong digital foundation while still requiring further capability development in several organizational dimensions.

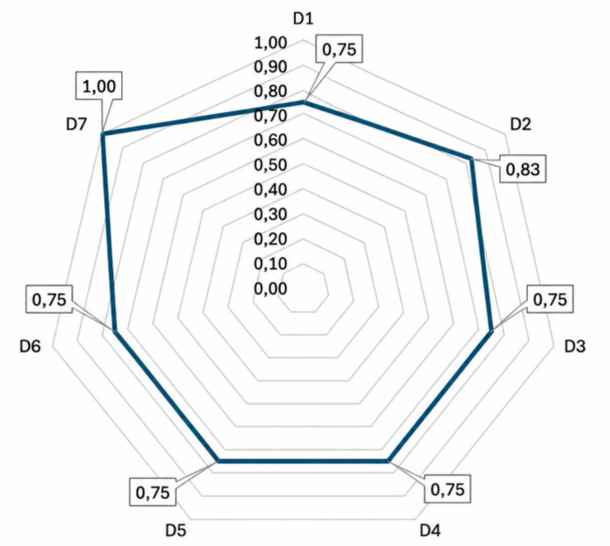

Figure 6. Industry 4.0 maturity scores across the seven dimensions

The radar profile reveals that digital maturity is not uniformly distributed across dimensions. While technological deployment has reached a relatively advanced stage, organizational capabilities such as customer integration, innovation, and change management remain areas requiring further strengthening. These findings indicate that the organization has implemented most of the key elements of Industry 4.0, including an integrated digital strategy, innovation practices, and the application of intelligent manufacturing technologies. However, to progress toward Stage 5 (Expert), the company needs to strengthen cross-system integration, enhance human resource competencies, and further exploit real-time data analytics and decision-support capabilities.

4.3 Contribution Analysis of Maturity Dimensions

To further understand the relative importance of each maturity dimension, the maturity scores obtained from the fuzzy inference process were multiplied by their respective AHP-derived weights. Table 8 presents the relative weighted contributions of each Industry 4.0 dimension based on the AHP-derived priority weights and the normalized maturity scores. These values are intended to illustrate the comparative influence of each dimension on the maturity assessment.

Table 8. Relative weighted contribution of the seven Industry 4.0 maturity dimensions

Dimension	Weight	Score	Weighted Contribution
Strategy	0.168	0.90	0.151
IT and Process Digitalization	0.131	0.83	0.109
Customers	0.136	0.75	0.102
Culture and Expertise	0.164	0.75	0.123
Organization and Change Management	0.159	0.75	0.119
Innovation	0.134	0.75	0.101
Intelligent Manufacturing	0.107	1.00	0.107

Note: Weighted Contribution = AHP Weight × Normalized Dimension Score. These values indicate the relative influence of each dimension and are not summed to obtain the final Industry 4.0 maturity index. The overall maturity index (0.73) was generated through FIS inference and defuzzification. IT = Information Technology; AHP = Analytic Hierarchy Process; FIS = Fuzzy Inference System.

Figure 7 illustrates the weighted contribution of each maturity dimension to the overall Industry 4.0 maturity index. Strategy generated the largest contribution (0.151), followed by Culture and Expertise (0.123) and Organization and Change Management (0.119). These results indicate that organizational and managerial capabilities play a central role in enabling digital transformation and substantially influence the effectiveness of technology implementation.

Although Intelligent Manufacturing achieved the highest maturity score (1.00), its overall contribution (0.107) remained relatively moderate because of its lower AHP weight. This finding suggests that advanced manufacturing technologies alone are insufficient to determine digital maturity. Rather, technological capabilities need to be supported by strategic orientation, organizational culture, and effective change management mechanisms.

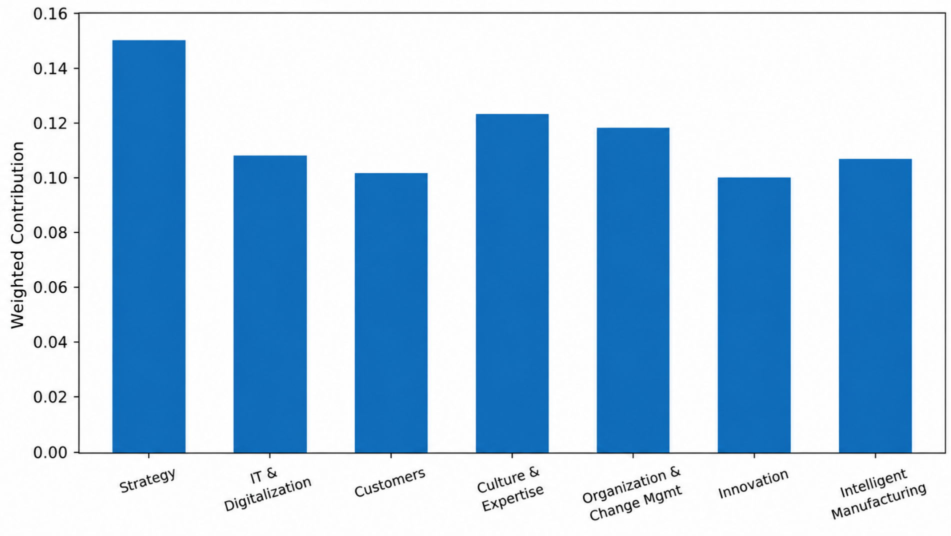

Figure 7. Weighted contribution of the seven maturity dimensions

The contribution analysis further demonstrates that Industry 4.0 maturity develops through a combination of interdependent organizational and technological capabilities. Dimensions associated with strategic planning and organizational readiness contribute more substantially to overall maturity than isolated technological deployment. Consequently, manufacturing organizations should prioritize investments in strategic capability development, workforce competencies, and change management initiatives while simultaneously strengthening technological integration and intelligent manufacturing practices.

4.4 Maturity Gap Analysis

To identify areas requiring further development, the current maturity scores were compared with the desired expert-level maturity target (1.00) across all dimensions. The resulting gaps indicate the extent of improvement necessary for each capability area to achieve full Industry 4.0 maturity (Table 9).

Table 9. Current and target maturity levels across dimensions

Dimension	Current	Target	Gap
Strategy	0.90	1.00	0.10
IT and Process Digitalization	0.83	1.00	0.17
Customers	0.75	1.00	0.25
Culture and Expertise	0.75	1.00	0.25
Organization and Change Management	0.75	1.00	0.25
Innovation	0.75	1.00	0.25
Intelligent Manufacturing	1.00	1.00	0.00

Note: IT = Information Technology.

Figure 8 compares the current and target maturity levels across the seven dimensions of the proposed Industry 4.0 framework. The analysis reveals heterogeneous capability gaps among the dimensions. Intelligent Manufacturing has already achieved the target maturity level and therefore exhibits no maturity gap. Strategy and IT and Process Digitalization demonstrate relatively small gaps of 0.10 and 0.17, respectively, indicating that these dimensions are approaching expert-level maturity.

Conversely, Customers, Culture and Expertise, Organization and Change Management, and Innovation exhibit the largest gaps (0.25 each). These findings suggest that the organization's remaining challenges are primarily associated with organizational capabilities rather than technological deployment. In particular, workforce competencies, change management practices, innovation capabilities, and customer integration mechanisms require further strengthening to support sustained digital transformation.

From an engineering management perspective, the maturity gap analysis provides a practical basis for prioritizing transformation initiatives and allocating resources. The results indicate that future improvement efforts should concentrate on capability development and organizational readiness, which function as critical enablers for the effective exploitation of digital technologies and the achievement of expert-level Industry 4.0 maturity.

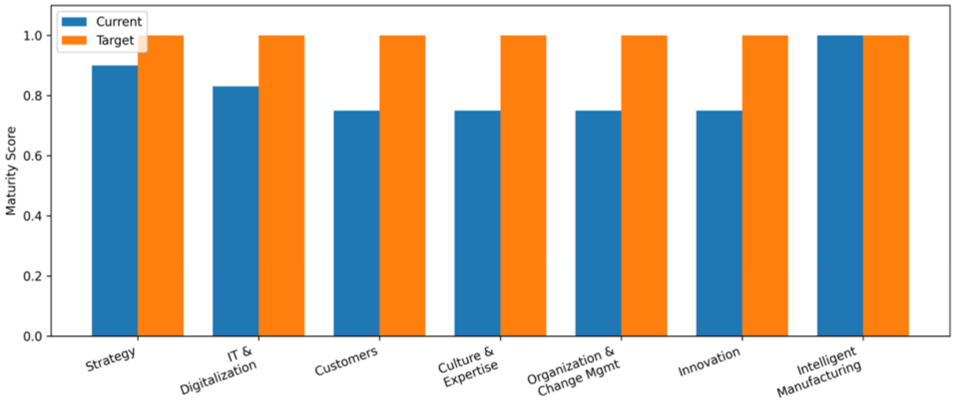

Figure 8. Current versus target maturity levels across dimensions

4.5 Sensitivity Analysis Results

To evaluate the robustness of the proposed framework, a sensitivity analysis was conducted by varying the AHP-derived weights under several alternative scenarios (Table 10). The analysis examined the effects of increasing and decreasing the most influential weights by 10%, as well as applying an equal-weighting assumption across all dimensions.

Table 10. Sensitivity analysis of the Industry 4.0 maturity index under alternative weighting assumptions

Scenario	Maturity Index	Stage
Original weights	0.73	Stage 4
Highest weights +10%	0.75	Stage 4
Highest weights -10%	0.71	Stage 4
Equal weighting assumption	0.72	Stage 4

Figure 9 presents the sensitivity analysis under alternative weighting assumptions. The maturity index varied only slightly, ranging from 0.71 to 0.75, despite moderate changes in the weighting structure. The highest maturity score (0.75) was obtained when the most influential dimensions received an additional 10% weight, whereas the lowest score (0.71) occurred when their weights were reduced by 10%.

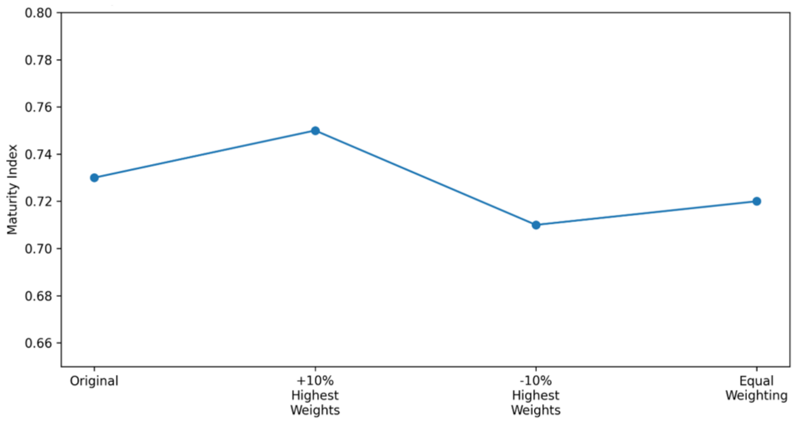

Figure 9. Sensitivity of the maturity index under alternative weighting assumptions

Importantly, the organization remained within the Stage 4 (Advanced) maturity classification under all scenarios. Although numerical variations were observed, the maturity stage did not change. These findings indicate that the proposed AHP–FIS framework is reasonably robust and not excessively sensitive to moderate variations in weighting assumptions.

From an engineering management perspective, the stability of the maturity classification suggests that the assessment results are not driven by arbitrary weighting decisions. Instead, the framework demonstrates sufficient resilience to support evidence-based decision-making and transformation planning. Consequently, managers can use the proposed maturity assessment with greater confidence when prioritizing digital initiatives and allocating resources for Industry 4.0 implementation.

4.6 Comparative Validation and Transferability

To position the proposed framework within the existing Industry 4.0 maturity literature, a comparative validation was conducted against several widely adopted maturity assessment frameworks. The comparison focused on the treatment of weighting mechanisms, uncertainty management, validation procedures, and decision-support capabilities (Table 11).

Table 11. Comparative validation of the proposed AHP–FIS framework and existing Industry 4.0 maturity models

Framework	Weighting Approach	Uncertainty Handling	Validation	Decision Support	Main Limitation
Industry 4.0 maturity model [17]	Equal weighting	No	Case study	Limited	Static and deterministic assessment
Acatech maturity index [20]	Descriptive scoring	No	Multiple industrial applications	Limited	Limited treatment of qualitative uncertainty
Fuzzy rule-based Industry 4.0 maturity model [19]	Expert-based weighting	Fuzzy rules	Supply chain case	Partial	Limited multidimensional coverage
Proposed AHP–FIS framework	Expert-derived AHP weighting	Full FIS	Automotive manufacturing case	Comprehensive	Requires further multi-case validation

Note: AHP = Analytic Hierarchy Process; FIS = Fuzzy Inference System.

Compared with existing maturity frameworks, the proposed AHP–FIS model provides additional capabilities through systematic criteria weighting, explicit treatment of qualitative uncertainty, and the incorporation of decision-support mechanisms for prioritizing digital transformation initiatives. Although the empirical validation was conducted using a single automotive manufacturing case, the framework architecture is transferable because its dimensions, weighting procedures, and fuzzy inference mechanisms are independent of specific industrial technologies and can therefore be adapted to other manufacturing contexts.

The comparative assessment further indicates that the proposed framework extends conventional maturity models by integrating organizational and technological dimensions within a unified decision-support architecture. In addition to measuring maturity levels, the framework enables organizations to identify priority dimensions, evaluate capability gaps, and assess the robustness of transformation scenarios. These features increase the practical relevance of the framework for engineering management applications in manufacturing environments.

Overall, the findings demonstrate that the integrated AHP–FIS framework provides a structured, consistent, and decision-oriented approach to Industry 4.0 maturity assessment. Beyond identifying organizational maturity levels, the framework enables contribution analysis, maturity gap identification, sensitivity evaluation, and the prioritization of transformation initiatives. These capabilities enhance its practical value as an engineering management tool for supporting evidence-based digital transformation planning and continuous capability development in manufacturing organizations.

5 Discussion

5.1 Interpretation of Industry 4.0 Maturity Dimensions

The AHP analysis revealed that Strategy, Culture and Expertise, and Organization and Change Management received the highest priority weights. This finding suggests that Industry 4.0 transformation is fundamentally an organizational capability development process rather than merely a technological implementation exercise. Although Intelligent Manufacturing achieved the highest maturity score in the case company, its relatively low weight indicates that advanced manufacturing technologies are perceived as outcomes of transformation that emerge after strategic alignment, capability development, and organizational readiness have been established.

This finding is consistent with previous studies that emphasize the critical role of organizational enablers in digital transformation. Schumacher et al. [17] and Gökalp and Martinez [6] argue that technological implementation frequently fails when organizations lack strategic commitment, digital competencies, and effective change management mechanisms. Therefore, the present results reinforce the proposition that digital maturity should be viewed as a socio-technical capability system in which managerial and organizational capabilities precede and enable technological advancement.

The maturity gap analysis further demonstrates that the organization has achieved high technological capability in Intelligent Manufacturing while still exhibiting deficiencies in customer integration, innovation capability, and organizational adaptability. This imbalance suggests that technological investments alone do not guarantee comprehensive digital transformation and that complementary organizational capabilities remain necessary for achieving expert-level maturity.

5.2 Systems Perspective of Industry 4.0 Maturity Development

The findings suggest that Industry 4.0 maturity evolves through interdependent and mutually reinforcing organizational and technological capabilities rather than through isolated dimensions. The contribution analysis revealed that Strategy, Culture and Expertise, and Organization and Change Management represent the principal enablers of digital transformation, indicating that organizational capabilities play a foundational role in determining digital maturity outcomes.

This systems perspective explains why dimensions with relatively lower maturity scores may substantially influence overall transformation performance. Deficiencies in organizational culture, employee competencies, or innovation capabilities can constrain the effectiveness of advanced manufacturing technologies despite considerable investments in digital infrastructure. Similar observations were reported by Senna et al. [5], who argued that digital transformation maturity emerges from dynamic interactions among technological, organizational, and environmental capabilities rather than from technological adoption alone.

Figure 10 illustrates the interdependency among the six maturity dimensions. Strategic commitment establishes digital priorities and investment directions, which subsequently shape organizational culture and capability development. These cultural and human capabilities facilitate organizational change management and enable more effective digitalization initiatives. The development of digital infrastructure then supports innovation capability and eventually leads to intelligent manufacturing implementation. Consequently, digital maturity should be managed as an integrated transformation process in which improvements in one dimension generate cascading effects on other dimensions.

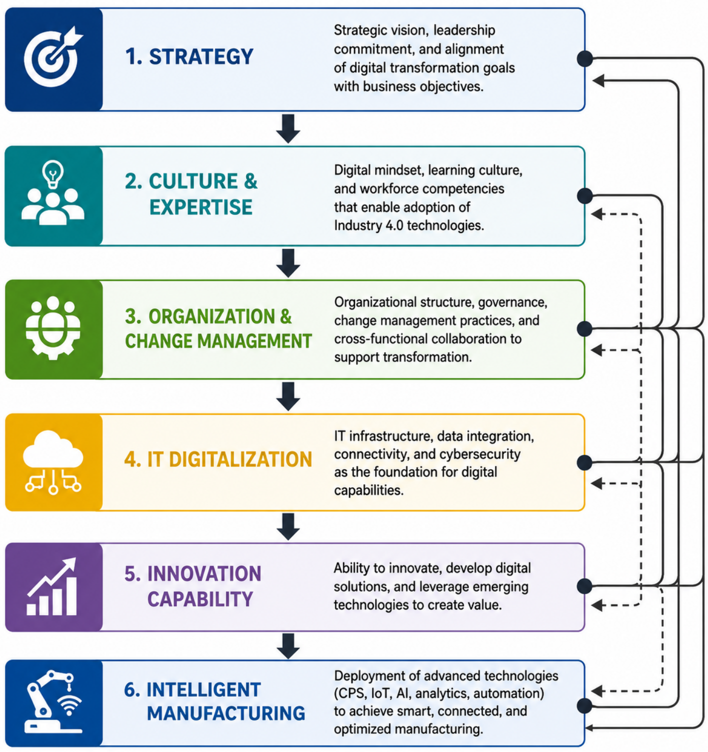

Figure 10. Interdependency of Industry 4.0 maturity dimensions

Note: IT = Information Technology; CPS = Cyber-Physical Systems; IoT = Internet of Things.

The proposed AHP–FIS framework contributes to this systems-oriented understanding by capturing both the relative importance of maturity dimensions and the nonlinear relationships among them. Beyond measuring organizational maturity, the framework provides decision support for identifying leverage points and prioritizing transformation initiatives capable of generating organization-wide capability development.

5.3 Methodological Contribution and Comparison with Existing Models

Compared with existing Industry 4.0 maturity frameworks, the proposed AHP–FIS model provides several methodological improvements. First, the use of expert-derived AHP weighting addresses the limitations of equal-weight and descriptive scoring approaches commonly found in previous maturity models. Second, the FIS explicitly accommodates uncertainty and linguistic assessments that characterize many organizational variables, including culture, readiness for change, and innovation capability.

Previous frameworks frequently rely on deterministic scoring mechanisms that may oversimplify the complexity of digital transformation assessment [14, 17]. By integrating structured weighting and fuzzy reasoning, the proposed framework provides a more adaptive and context-sensitive maturity evaluation process. The sensitivity analysis further demonstrated that moderate variations in weighting assumptions did not alter the overall maturity classification, indicating that the framework possesses reasonable robustness and practical reliability [21].

Beyond maturity scoring, the framework also enables contribution analysis, maturity gap identification, and prioritization of transformation initiatives. These additional analytical capabilities differentiate the proposed framework from many existing maturity models that primarily function as diagnostic assessment instruments.

5.4 Managerial Implications and Future Development

From an engineering management perspective, the findings indicate that maturity assessment should serve as a decision-support mechanism rather than merely a measurement instrument. The weighted contribution analysis enables managers to identify dimensions that exert the greatest influence on organizational maturity, while maturity gap analysis assists in determining capability areas requiring immediate intervention.

The proposed framework also supports the sequencing of digital transformation initiatives. Organizations may prioritize investments in strategic alignment, digital competencies, and change management capabilities before allocating substantial resources to advanced manufacturing technologies. Such sequencing can reduce implementation risks, improve resource allocation efficiency, and increase the probability of successful digital transformation.

Nevertheless, several limitations should be acknowledged. The empirical validation was conducted using a single automotive manufacturing case, which limits the generalizability of the findings. In addition, the framework remains partially dependent on expert judgments in criteria weighting and fuzzy rule development. Future research should therefore validate the framework across multiple industrial sectors, involve larger and more diverse expert panels, and explore the integration of advanced analytical techniques, such as machine learning and adaptive fuzzy systems, to further refine maturity assessment and transformation planning capabilities.

6 Conclusion

This study demonstrates that the integration of the AHP and the FIS provides a feasible methodological approach for evaluating Industry 4.0 digital maturity in manufacturing organizations. The AHP method enables the systematic derivation of priority weights among maturity dimensions, whereas the FIS accommodates uncertainty and subjectivity inherent in qualitative assessments. The integration of both methods produces a multidimensional and adaptive maturity evaluation framework that captures the complexity of digital transformation processes more comprehensively than conventional deterministic assessment approaches.

The empirical application of the framework in an automotive parts manufacturing company produced an overall maturity index of 0.73, placing the organization at Stage 4 (Advanced). The findings indicate that although advanced digital capabilities have been established, additional improvements remain necessary in strategic alignment, organizational capability development, and cross-functional integration to achieve expert-level digital maturity.

This study offers three principal contributions. Theoretically, it enriches the Industry 4.0 maturity literature by conceptualizing digital maturity as an interdependent socio-technical capability system rather than merely a technology adoption process. Methodologically, it proposes an integrated AHP–FIS framework that combines systematic criteria weighting and explicit treatment of qualitative uncertainty while supporting contribution analysis, maturity gap identification, and sensitivity evaluation. Practically, the framework demonstrated practical feasibility in the investigated automotive manufacturing case and may serve as a preliminary assessment framework for similar manufacturing environments requiring evidence-based digital transformation planning and prioritization.

Several limitations should be acknowledged. The empirical validation was conducted in a single automotive manufacturing organization and therefore does not permit broad generalization across manufacturing sectors or industrial contexts. Furthermore, the weighting procedures and fuzzy rule base remain partially dependent on expert judgments and contextual assumptions.

Future studies should therefore validate the framework through multi-case and cross-industry investigations, perform longitudinal assessments to examine maturity evolution over time, and explore the integration of machine learning and adaptive fuzzy techniques to further improve the robustness, scalability, and predictive capability of Industry 4.0 maturity assessment frameworks.

Author Contributions

Conceptualization, A.C.N. and T.A.; methodology, A.C.N. and T.A.; formal analysis, A.C.N. and A.H.P.; investigation, A.C.N., T.A., and A.H.P.; data curation, A.C.N.; writing—original draft preparation, A.C.N.; writing—review and editing, T.A. and A.H.P.; visualization, A.C.N.; supervision, T.A. and A.H.P. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to confidentiality agreements with the participating manufacturing organization, the raw data are not publicly available.

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Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Appendix

Appendix A. Representative expert-validated fuzzy rule base for Industry 4.0 maturity assessment

The fuzzy rule base consists of 72 expert-validated rules developed through a four-stage procedure involving: (1) initial rule generation based on the literature and the seven Industry 4.0 maturity dimensions, (2) independent expert review, (3) resolution of conflicting rule consequents through iterative discussion, and (4) consensus validation of the final rule base.

The linguistic terms used in the antecedent variables are: VL = Very Low, L = Low, M = Medium, H = High, and VH = Very High. The consequent variable (Output Stage) represents the maturity classification ranging from Stage 1 (Novice) to Stage 5 (Expert).

Table A1. Representative expert-validated fuzzy rule base for Industry 4.0 maturity assessment

No.	Strategy	IT and Process Digitalization	Customers	Culture and Expertise	Organization and Change Management	Innovation	Intelligent Manufacturing	Output Stage
1	VH	H	VH	H	H	H	H	4
2	H	M	H	H	M	M	L	3
3	M	M	H	M	M	M	M	3
4	H	H	H	VH	H	H	M	4
5	H	VH	H	H	H	H	VH	4
6	M	H	M	H	H	H	H	4
7	H	M	L	M	H	H	L	3
8	VH	VH	VH	H	H	H	H	4
9	VH	H	H	VH	H	VH	H	5
10	H	H	M	H	H	H	M	4
11	H	M	H	H	H	M	M	3
12	M	H	H	H	M	H	M	3
...	...	...	...	...	...	...	...	...
71	H	H	H	VH	H	VH	VH	4
72	VH	M	VH	VH	H	H	H	4

Note: IT = Information Technology.

Due to space limitations, Appendix A presents a representative subset of the expert-validated fuzzy rule base. 72 fuzzy inference rules used in this study are available from the corresponding author upon reasonable request.

The theoretically possible combinations of seven input variables with five linguistic terms are 5^7 = 78,125 rule combinations. However, an exhaustive rule base would be computationally impractical and would include numerous unrealistic industrial scenarios. Therefore, the final rule base was restricted to 72 representative and expert-validated rules that capture the most plausible maturity configurations observed in manufacturing organizations.

Appendix B. Questionnaire items used for Industry 4.0 maturity assessment

All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Table B1. Questionnaire items for Industry 4.0 maturity assessment

Dimension	Code	Questionnaire Item
Strategy	ST1	The organization has a formal digital transformation strategy.
	ST2	Industry 4.0 initiatives are aligned with business objectives.
	ST3	Digital transformation investments are supported by top management.
	ST4	Digital transformation priorities are clearly communicated throughout the organization.
IT and Process Digitalization	IT1	Core business processes are digitally integrated.
	IT2	Manufacturing operations are supported by real-time information systems.
	IT3	Data are centrally stored and accessible across departments.
	IT4	The organization has adequate cybersecurity mechanisms.
Customers	CU1	Customer requirements are systematically collected and analyzed.
	CU2	Digital technologies are used to improve customer interactions.
	CU3	Customer feedback is incorporated into decision-making processes.
	CU4	Advanced analytics are utilized to understand customer behavior.
Culture and Expertise	CE1	Employees possess adequate digital competencies.
	CE2	The organization regularly provides digital skills training.
	CE3	The organizational culture supports innovation and experimentation.
	CE4	Employees are encouraged to adopt new digital technologies.
Organization and Change Management	OC1	The organization effectively manages digital transformation initiatives.
	OC2	Cross-functional collaboration supports digital transformation activities.
	OC3	Employees actively participate in organizational change initiatives.
	OC4	Organizational structures facilitate digital transformation implementation.
Innovation	IN1	The organization continuously develops digital innovations.
	IN2	Digital technologies are utilized to improve products and services.
	IN3	Innovation initiatives are supported by adequate resources.
	IN4	Customers and external partners participate in innovation activities.
Intelligent Manufacturing	IM1	Manufacturing systems employ advanced automation technologies.
	IM2	Production systems are capable of real-time monitoring and control.
	IM3	Manufacturing equipment is digitally interconnected.
	IM4	Manufacturing operations utilize data analytics for decision support.

Appendix C. Sensitivity analysis of the proposed Analytic Hierarchy Process–Fuzzy Inference System (AHP–FIS) framework

The robustness of the proposed AHP–FIS framework was examined by evaluating alternative weighting assumptions. The weights of the three most influential dimensions (Strategy, Culture and Expertise, and Organization and Change Management) were increased and decreased by 10%, while an equal-weighting scenario was also considered. The resulting maturity indices were compared with the baseline results.

Table C1. Sensitivity analysis under alternative weighting assumptions

Scenario	Maturity Index	Maturity Stage	Change from Baseline
Original AHP weights	0.73	Stage 4	–
Highest weights +10%	0.75	Stage 4	+0.02
Highest weights -10%	0.71	Stage 4	-0.02
Equal weighting assumption	0.72	Stage 4	-0.01

Note: AHP = Analytic Hierarchy Process. "–" indicates the baseline scenario; therefore, no change from the baseline is applicable.

The results indicate that the maturity index remained within Stage 4 under all alternative weighting assumptions. Although small numerical variations were observed, no changes occurred in the maturity classification. These findings suggest that the proposed AHP–FIS framework is reasonably robust and not excessively sensitive to moderate variations in weighting assumptions.