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Designing a Causal–Stage Model of Artificial Intelligence–Based World-Class Total Productive Maintenance for the Iranian Automotive Industry

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Abstract

In the era of Industry 5.0, the transformation of Total Productive Maintenance (TPM) in the automotive industry extends far beyond the adoption of conventional maintenance practices or the fragmented use of artificial intelligence applications. Such a transformation requires an integrated model that explains how AI-based maintenance capabilities should be identified, causally structured, sequenced, and translated into an executable architecture for achieving world-class performance. Although research on intelligent maintenance and predictive analytics has expanded considerably, much of the existing literature has focused on algorithmic accuracy, condition monitoring, or narrowly defined technological applications, while paying limited attention to how artificial intelligence capabilities can be structured and implemented to support World-Class Total Productive Maintenance. To address this gap, the present study designs a causal–stage model of Artificial Intelligence–Based World-Class Total Productive Maintenance (AI-WCTPM) for the Iranian automotive industry. The findings reveal a six-level architecture in which the real-time communication network and cyber–physical security constitute the foundational layer; edge processing and smart sensors form the perception and data-processing layer; intelligent knowledge management functions as the central knowledge platform; dynamic failure prediction and resilient supply chain operate as advanced analytical engines; preventive quality control and intelligent continuous improvement constitute the optimization and action layer; and world-class performance indicators represent the final outcome layer. The proposed AI-WCTPM model integrates causal influence, implementation sequencing, AI-tool alignment, and performance monitoring into a coherent data–knowledge–decision architecture. Expert validation confirms the structural coherence, content adequacy, and practical applicability of the model. This study advances intelligent maintenance research by shifting the focus from isolated algorithmic applications toward a stage-based architecture for World-Class TPM and provides automotive managers with a structured roadmap for prioritizing AI investments, reducing implementation risk, and aligning maintenance transformation with world-class performance objectives.

Keywords: Automotive Industry; Artificial Intelligence; Total Productive Maintenance; World-Class Management

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1. Introduction

The automotive industry is one of the most technologically intensive and operationally complex manufacturing environments, characterized by continuous production flows, highly interdependent equipment, large numbers of components and suppliers, stringent quality requirements, short delivery cycles, and substantial pressure to control production costs. Within such a system, equipment reliability and maintenance effectiveness have direct consequences for productivity, quality, safety, delivery performance, energy use, and competitiveness. Unplanned equipment failures can interrupt entire production lines, generate bottlenecks, increase repair and labor costs, create defective products, and compromise delivery commitments. Consequently, maintenance can no longer be regarded merely as a technical support function concerned with restoring equipment after failure. It has increasingly become a strategic organizational capability that must be aligned with production strategy, asset management, quality management, and long-term competitive priorities (Tsang, 2002). This strategic interpretation is particularly important in the automotive sector, where the economic effects of even short periods of downtime can propagate rapidly through interconnected production and supply systems.

Total Productive Maintenance (TPM) has emerged as one of the major managerial approaches for addressing these challenges by integrating maintenance activities with employee participation, autonomous maintenance, planned maintenance, equipment effectiveness, quality improvement, and continuous improvement. The central philosophy of TPM is to maximize the effectiveness of production assets by reducing breakdowns, defects, minor stoppages, speed losses, and other equipment-related inefficiencies. Evidence from manufacturing environments indicates that effective TPM implementation is associated with improvements in key performance indicators such as equipment availability, productivity, maintenance efficiency, failure reduction, quality, and organizational performance (Toke & Kalpande, 2023). Moreover, TPM has long been recognized as an important mechanism through which manufacturing firms can progress toward world-class status, because it creates the equipment reliability and process stability required for high-quality, low-cost, responsive production systems (Farsijani et al., 2012). From a World-Class Manufacturing perspective, maintenance therefore contributes not only to equipment performance but also to broader objectives such as customer value, operational excellence, competitive quality, cost efficiency, and production responsiveness (Farsijani & Dehghan, 2016).

However, the requirements of contemporary manufacturing increasingly exceed the capabilities of conventional TPM approaches. The rapid development of cyber–physical systems, industrial Internet of Things technologies, artificial intelligence, advanced sensing, cloud and edge computing, digital twins, and data-driven decision systems has fundamentally changed the technological environment in which maintenance activities are performed. Industry 4.0 has enabled equipment and manufacturing systems to generate large volumes of real-time operational data, while the emerging Industry 5.0 perspective further emphasizes intelligent, resilient, sustainable, and human-centered manufacturing. Within this transformation, maintenance is shifting from scheduled and experience-based intervention toward connected, condition-based, predictive, prescriptive, and increasingly autonomous decision-making. Research on the digitalization of maintenance demonstrates that Industry 4.0 technologies can substantially strengthen TPM practices when technological adoption is systematically integrated with maintenance processes rather than introduced as isolated digital initiatives (Tortorella et al., 2024). Similarly, the integration of TPM with Industry 4.0 requires a structured framework capable of linking technological capabilities with standardized maintenance practices and organizational processes (Mouhib et al., 2025).

Artificial intelligence represents a central enabling mechanism in this transformation. AI-based maintenance systems can process high-frequency sensor signals, identify abnormal equipment behavior, classify failure patterns, predict remaining useful life, support maintenance scheduling, analyze images for defects, extract knowledge from technical documents, and assist managers in selecting corrective or preventive interventions. Predictive maintenance has consequently become one of the most important applications of artificial intelligence in smart manufacturing. Reviews of predictive maintenance research demonstrate that machine learning and AI techniques can support failure anticipation and reduce dependence on traditional corrective or purely time-based maintenance, although significant challenges remain concerning data availability, model generalization, computational requirements, implementation complexity, and industrial scalability (Achouch et al., 2022; Hector & Panjanathan, 2024; Taoufyq et al., 2025). Thus, the technological potential of predictive maintenance is substantial, but its practical value depends on whether algorithms can be embedded within a coherent operational architecture.

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Recent developments in deep learning have further expanded the analytical capabilities available to maintenance systems. Architectures based on convolutional neural networks, recurrent networks, transformers, autoencoders, and other deep-learning methods can recognize complex temporal and spatial patterns that may remain undetected by conventional statistical techniques (Li et al., 2024). Data-driven predictive maintenance studies in automotive environments have also shown that the practical effectiveness of AI depends not merely on selecting an accurate algorithm but on understanding industrial data characteristics, building appropriate feature and data pipelines, and translating analytical results into operational decisions (Giordano et al., 2022). Intelligent manufacturing systems therefore require a transition from an algorithm-centered view of predictive maintenance toward an architecture-centered view in which equipment data, processing, knowledge, prediction, decision-making, and feedback are systematically connected.

This architectural perspective has become increasingly important because contemporary manufacturing data are generated at multiple levels and must often be processed with very low latency. Industrial Internet of Things infrastructures and edge–cloud architectures allow sensor information to be captured near production equipment, processed locally when rapid responses are necessary, and transmitted to higher-level analytical platforms for more sophisticated computations and knowledge accumulation (Somu & Dasappa, 2025). Similarly, high-performance data infrastructures are becoming important for accelerating visual anomaly detection and other data-intensive applications in smart manufacturing (Wang & Liang, 2025). Digital twins provide another important mechanism for integrating physical assets, real-time information, predictive models, and decision processes. Data-driven digital-twin frameworks can support predictive maintenance by continuously connecting equipment states with analytical models and maintenance decisions (Khan et al., 2025). These advances indicate that intelligent maintenance performance increasingly depends on the architecture connecting data acquisition, communication, computation, analytics, and action.

Knowledge management constitutes another critical component of such an architecture. Industrial maintenance organizations accumulate substantial knowledge in work orders, technician reports, failure histories, operating manuals, maintenance procedures, engineering documents, and corrective-action records. Yet much of this information remains unstructured and difficult to reuse in real-time decision-making. Recent developments in natural language processing and causal knowledge extraction demonstrate that maintenance documents can be transformed into structured knowledge capable of supporting diagnostic and decision processes (Hershowitz et al., 2024). Accordingly, AI-based maintenance should not be limited to sensor-based prediction. It should also integrate historical experience and organizational knowledge with real-time operational information. The combination of equipment data and accumulated maintenance knowledge provides a more comprehensive basis for failure prediction, intervention planning, root-cause analysis, and continuous organizational learning.

The integration of maintenance with product quality is equally important in automotive production. Equipment degradation can manifest not only through catastrophic breakdowns but also through gradual deviations in process conditions that increase defects, dimensional variation, rework, and scrap. Therefore, an advanced maintenance system should link equipment condition with quality information so that emerging deterioration can be identified before it results in significant production losses. Research integrating machine learning-based predictive maintenance with product-quality parameters illustrates the value of combining maintenance and quality information to optimize maintenance interventions (Riccio et al., 2024). Intelligent quality control thus represents a natural extension of predictive maintenance, transforming AI-generated insight from a diagnostic output into a preventive operational mechanism that contributes directly to world-class performance.

Furthermore, maintenance performance is increasingly interconnected with supply-chain resilience. Predicting a component failure has limited operational value if required spare parts, tools, personnel, or external services are unavailable when intervention is needed. Intelligent maintenance therefore requires coordination between failure prediction and resource or supply decisions. Advanced optimization approaches, including reinforcement learning combined with graph-based models, demonstrate the potential of artificial intelligence for solving complex network and routing problems and supporting adaptive decision-making in interconnected supply systems (Wang et al., 2025). Such capabilities are relevant to World-Class TPM because equipment reliability depends not only on detecting technical deterioration but also on ensuring that maintenance resources can be mobilized efficiently and resiliently.

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For automotive manufacturers operating in developing and emerging industrial environments, however, technological transformation is constrained by organizational readiness, infrastructure maturity, digital integration, investment capacity, and access to reliable data. In the Iranian automotive industry, digital transformation requires coordinated development of technological infrastructure, organizational processes, information integration, and Industry 4.0 capabilities (Mozaffari Mehr & Taghavi Fard, 2024). Research concerning the implementation of fourth-generation industry principles in the Iranian automotive sector similarly emphasizes the need to integrate technological transformation with broader sustainability and organizational objectives (Ardehi et al., 2023). These conditions make the Iranian automotive industry an important context for examining how artificial intelligence can be incorporated into TPM through a realistic and sequential implementation model rather than through fragmented adoption of advanced technologies.

A further issue concerns how world-class maintenance performance should be evaluated. Advanced maintenance transformation is meaningful only if technological capabilities eventually contribute to measurable organizational outcomes. World-Class Manufacturing assessment approaches emphasize the progressive development of organizational capabilities and the use of performance measures to evaluate movement toward superior manufacturing maturity (de Andrade et al., 2021). In the maintenance domain, relevant outcomes include reductions in mean time to repair, failure frequency, maintenance cost, and production scrap, together with improvements in equipment availability and Overall Equipment Effectiveness. Intelligent maintenance architecture should therefore establish an explicit connection between technological inputs and these performance outcomes. Predictive systems, for example, should not be evaluated solely according to classification accuracy; they should ultimately be assessed according to their capacity to improve operational reliability, quality, cost, and productivity. Practical intelligent manufacturing implementations similarly demonstrate the importance of designing predictive maintenance systems around operational decision requirements rather than treating analytical models as independent technical artifacts (Cinar et al., 2022).

Despite these developments, an important research gap remains. Much of the current literature investigates individual technologies, predictive algorithms, sensing systems, digital twins, anomaly-detection techniques, or specific Industry 4.0 applications. These studies provide valuable technological knowledge, but they do not necessarily explain how multiple AI-based capabilities should be causally related, prioritized, and sequenced to create an integrated World-Class TPM system. The challenge is therefore not simply to determine whether artificial intelligence can improve maintenance, but to identify which capabilities must be established first, which factors act as enabling infrastructure, which function as analytical or operational levers, and how they should collectively lead to world-class outcomes. The foundational study underlying the present research identified a set of interconnected AI-based World-Class TPM components for the automotive industry and demonstrated that these components differ in their causal influence and functional roles (Mohammadi Rad et al., 2026). The remaining methodological and managerial challenge is to transform these interdependencies into a coherent stage-based implementation architecture.

Multi-criteria structural modeling methods provide an appropriate foundation for addressing this challenge. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is particularly useful for identifying the intensity and direction of relationships among interdependent factors and distinguishing influential factors from dependent ones. However, the interpretation of DEMATEL results depends strongly on the determination of meaningful relationship thresholds; methodological research has therefore examined procedures for identifying defensible threshold values when converting influence matrices into interpretable structures (Ebrahimi, 2023). DEMATEL has been successfully applied to complex multi-criteria systems in which the objective is to understand causal influence among interconnected dimensions (Nyimbili et al., 2023). Nevertheless, causal influence alone does not establish the logical sequence in which organizational capabilities should be implemented.

Interpretive Structural Modeling (ISM) complements this limitation by transforming interrelationships among factors into hierarchical levels and identifying prerequisite, intermediate, and outcome elements. Recent integrated approaches combining DEMATEL with ISM and related analytical methods demonstrate that causal influence networks can be converted into structured hierarchical models that offer more actionable managerial interpretations (Li et al., 2025). For AI-based TPM, this distinction is crucial: the component exerting the strongest causal influence is not necessarily the component that should be

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implemented first. Advanced predictive analytics may exert considerable influence on maintenance outcomes, but such analytics cannot operate sustainably without communication networks, secure data exchange, reliable sensing, and appropriate processing infrastructure. A causal-stage model must therefore integrate both influence intensity and implementation dependency.

Accordingly, the conceptual challenge facing contemporary automotive maintenance is to move beyond independent predictive-maintenance applications toward an integrated data–knowledge–decision architecture. Such an architecture should begin with reliable communication and cyber–physical infrastructure, develop sensing and edge-processing capabilities, transform operational information into accessible organizational knowledge, employ advanced analytical mechanisms for failure prediction and resilient decision-making, connect analytical outputs with preventive quality control and continuous improvement, and finally evaluate the resulting effects through world-class maintenance and manufacturing indicators. This staged perspective addresses the fragmented character of much existing intelligent-maintenance research and provides a bridge between artificial intelligence, TPM, and World-Class Manufacturing.

Therefore, the aim of this study is to design a causal–stage model of Artificial Intelligence–Based World-Class Total Productive Maintenance (AI-WCTPM) for the Iranian automotive industry by integrating the causal influence of validated components, their hierarchical implementation sequence, corresponding artificial intelligence capabilities, and world-class performance outcomes.

2. Methods and Materials

The present study is applied–developmental in terms of purpose and structural–modeling and expert-based in terms of strategy. Its purpose is to design a causal–stage model of Artificial Intelligence–Based World-Class Total Productive Maintenance for the Iranian automotive industry. The article is based on the outputs of a study that extracted nine core components, six world-class outcome indicators, the crisp total-relation matrix T, the D, R, D+R, and D−R indices, and meaningful fuzzy DEMATEL relationships (Mohammadi Rad et al., 2026). Therefore, the unit of analysis in the present article is validated relationships and influence intensity among factors, not the re-extraction of components. The research process was designed in six steps. In the first step, the outputs of fuzzy DEMATEL, including the crisp total-relation matrix T, the threshold value, the intensity of relationships, and the causal/dependent role of components, were used. In the second step, matrix T was converted into a binary matrix. In the third step, the final reachability matrix was formed using transitive closure and Boolean logic. In the fourth step, the reachability set, antecedent set, and intersection set were extracted for each factor, and ISM levels were determined. After extracting the levels, threshold sensitivity analysis was performed to assess the stability of the ISM structure. In the fifth step, ISM levels, causal roles of components, DEMATEL relationship intensities, and the AI tools corresponding to each component were transformed into the architectural layers of AI-WCTPM. In the sixth step, the final model—consisting of the ISM level structure, DEMATEL causal roles, executable architecture based on component-specific AI tools, and the data/knowledge/decision flow—was validated by experts.

The input of this article consists of 15 factors: nine core components and six world-class outcome indicators. The nine core components are coded as A1 to A9, and the six outcome indicators are coded as B1 to B6. These factors are introduced in Table 1.

Table 1. Input factors of the causal–stage model

Code	Factor	Corresponding AI Tool/Logic	Causal Role of the Component
A1	Real-time communication network	GNN and industrial communication infrastructure	Enabling infrastructure; foundation of data flow and communication
A2	Edge processing	Compressed DNN and Edge AI	Supporting cause; enables processing close to equipment
A3	Smart sensors	1D-CNN and signal analysis	Data-acquisition infrastructure; enables equipment-state perception
A4	Dynamic failure prediction	LSTM + Attention	Strong causal lever; engine for prediction and early intervention
A5	Preventive quality control	YOLOv8 and computer vision	Strong causal lever; links maintenance and quality
A6	Intelligent knowledge management	Transformer/NLP	Supporting cause; converts data and experience into decision-ready knowledge
A7	Resilient supply chain	GNN + RL	Strong causal lever; supports maintenance action and parts supply

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A8	Intelligent continuous improvement	Autoencoder + XGBoost	Strong causal lever; converts analysis into correction and learning
A9	Cyber–physical security	Anomaly-detection DNN	Enabling infrastructure; protects data, equipment, and operations
B1	Reduction of mean time to repair	Performance indicator	World-class dependent outcome
B2	Increase in service availability ratio	Performance indicator	World-class dependent outcome
B3	Reduction of failure rate	Performance indicator	World-class dependent outcome
B4	Reduction of maintenance costs	Performance indicator	World-class dependent outcome
B5	Increase in Overall Equipment Effectiveness	Performance indicator	World-class dependent outcome
B6	Reduction of production scrap	Performance indicator	World-class dependent outcome

In the base study, the crisp total-relation matrix T showed the direct and indirect influence intensity among factors. Therefore, the present article does not re-estimate causal relationships. Rather, it uses the intensities embedded in T to extract meaningful relationships, perform binarization, conduct level structuring, and design the final architecture. This point is methodologically important because the present article uses the output of causal analysis as input data for designing the stage-based model. Accordingly, the doctoral dissertation by Mohammadi Rad et al. (2026) is used as one of the main sources.

To enter ISM, the crisp matrix T must be converted into a binary matrix. In the base study, the threshold value was determined based on the median of the non-zero off-diagonal elements of matrix T and was more defensible than the mean or mean ± standard deviation because of its greater robustness to outliers. The comparison of thresholding criteria is reported in the findings section so that this stage can be observed as a method-oriented finding of the study rather than merely as a methodological instruction. The binarization rule was defined as follows:

For $i \neq j$:

If $t_{ij} \geq \theta$, then $a_{ij} = 1$

If $t_{ij} < \theta$, then $a_{ij} = 0$

For $i = j$:

$a_{ii} = 1$

In this relationship, t_{ij} is the element of the crisp total-relation matrix T, θ is the threshold value, and a_{ij} is the corresponding element in the binary matrix A. The main diagonal was set equal to 1 to preserve reflexivity in the reachability matrix. The logic of this stage is that only relationships meaningful in terms of influence intensity enter the hierarchical structure, while weak relationships are removed.

After forming the initial binary matrix A, the final reachability matrix M was calculated using transitive closure. Transitive closure indicates that if factor i influences factor j and factor j influences factor k, then factor i also indirectly reaches factor k. To calculate these indirect relationships, Boolean multiplication and the Warshall algorithm were used. The Warshall algorithm is one of the classical methods for calculating transitive closure in Boolean matrices (Warshall, 1962). The general rule for forming the final reachability matrix is as follows:

$$M = A + A^2 + A^3 + \ldots + A^k$$

In this relationship, addition and multiplication are performed based on Boolean logic, and the calculation continues until the matrix no longer changes in the next iteration. At that point, the matrix reaches a stable state and the final reachability matrix is formed.

After forming the final reachability matrix, three sets were extracted for each factor: the reachability set, the antecedent set, and the intersection set. The reachability set R_i includes the factor itself and the factors that are reachable from it. The antecedent set P_i includes the factor itself and the factors that can reach it. The intersection set I_i is obtained from the intersection of the reachability and antecedent sets. The formulas are defined as follows:

$$R_i = \{j \mid m_{ij} = 1\}$$

$$P_i = \{j \mid m_{ji} = 1\}$$

$$I_i = R_i \cap P_i$$

The rule of level structuring in ISM is that if, for a factor, the reachability set equals the intersection set, that factor is placed at the highest remaining level:

$$R_i = I_i$$

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After determining the first-level factors, these factors are removed from the matrix, and the process is repeated for the remaining factors until all factors are leveled. In this article, ISM is not considered the final model. Rather, it is a level-structuring model and an intermediate stage that converts DEMATEL relationships into an implementation sequence. The final model is designed in the next step by integrating ISM level structuring, DEMATEL relationship intensity, causal roles of components, corresponding AI tools, and the data/knowledge/decision flow.

After extracting the ISM levels, threshold sensitivity analysis was conducted. In this analysis, the main threshold value θ was examined under two scenarios: a 5% decrease and a 5% increase. The aim was to determine whether the hierarchical ISM structure depends on a specific numerical threshold value or remains stable under limited threshold variations. In this article, threshold sensitivity analysis was conducted before designing the final architecture because the stability of ISM levels must be checked before mapping them into architectural layers.

After ISM level structuring and checking structural stability through sensitivity analysis, the extracted levels were converted into architectural layers. The logic of architecture design was based on the principle that each ISM level should be translated into an interpretable executable function. However, the architectural mapping was not derived from ISM alone. Rather, it was formed by integrating three foundations: first, the causal role and influence intensity of components in fuzzy DEMATEL; second, the implementation sequence and component levels in ISM; and third, the AI tools corresponding to each component and the data/knowledge/decision flow. The final AI-WCTPM model is not merely an ISM diagram. It simultaneously integrates three types of outputs: first, the intensity and direction of causal relationships derived from fuzzy DEMATEL; second, the level structure and implementation sequence of factors derived from ISM; and third, the executable architecture based on the AI tools of each component, including the data flow, knowledge flow, decision flow, and continuous improvement feedback loop. In the architecture design, the data flow starts from sensors, networks, and edge processing. The knowledge flow is formed through recording, extracting, and retrieving operational experiences and data. The decision flow passes through analytical and optimization engines and is connected to performance control and continuous improvement.

After designing the final architecture, the model was evaluated by experts. At this stage, the final AI-WCTPM model—not merely the ISM level structure—was evaluated in terms of comprehensiveness, logical coherence, applicability in the Iranian automotive industry, adequacy of the artificial intelligence architecture, expected influence on world-class indicators, and overall validity. The acceptance criteria included a minimum mean of 3.5, standard deviation below 1, and a Content Validity Index greater than 0.79. These three criteria were used complementarily to assess the level of acceptance, the degree of expert agreement, and the content adequacy of the model.

3. Findings and Results

In response to the first research question—how the influence intensity of components and the crisp total-relation matrix derived from fuzzy DEMATEL can be transformed into a structure suitable for stage-based modeling—the crisp total-relation matrix T was converted into a binary matrix using a thresholding criterion, and the final reachability matrix was then formed through transitive closure for entry into ISM.

To convert the crisp total-relation matrix T into a binary matrix, four thresholding criteria were examined. The values and the number of remaining relationships in Table 2 were taken from the outputs of Mohammadi Rad et al.'s doctoral dissertation (2026). The references in the final column support thresholding methods and their applications in decision-making studies.

Table 2. Comparison of thresholding criteria for binarizing matrix T

Threshold Criterion	Value	Number of Remaining Relationships	Structural Condition	Sensitivity to Outliers	Result	Supporting Reference
Mean + standard deviation	0.082	32	Very sparse	Highly sensitive	Inappropriate	Li et al., 2025
Mean	0.054	58	Relatively logical	Sensitive	Acceptable	Nyimbili et al., 2023
Median	0.044	72	Logical	Robust	Selected	Ebrahimi, 2023
Mean − standard deviation	0.026	104	Very dense	Highly sensitive	Inappropriate	Ebrahimi, 2023

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Based on Table 2, the median threshold was selected as the basis for binarization because it creates an appropriate balance between preserving key relationships and preventing excessive network density. This selection is also consistent with the purpose of the present article, because ISM should provide an interpretable structure for implementation, not an excessively dense or excessively sparse network. Based on the selected threshold, the crisp total-relation matrix T was converted into a binary matrix. At this stage, every relationship in matrix T with a value equal to or greater than the threshold was converted to 1, while weaker relationships were converted to 0. The main diagonal of the matrix was also set to 1 to preserve the reflexivity of the factors. The result of this stage was a 15 × 15 binary matrix, which served as the input for ISM calculations. Interpretively, binarization allowed the relationship network to move from the level of numerical DEMATEL intensities to the level of structural relationships. Therefore, DEMATEL showed which relationships had higher intensity, while ISM showed how these relationships were positioned within a hierarchical structure.

In response to the second research question—at which levels the core components and world-class outcome indicators are positioned and what their logical implementation sequence is—the final reachability matrix was analyzed, and the level structure of the factors was extracted using ISM rules. After applying transitive closure, the final reachability matrix was formed. Then, the reachability set, antecedent set, and intersection set were extracted for each factor. Based on the rule Ri = Ii, the factors were leveled. The final level-structuring results are presented in Table 3.

Table 3. Final ISM level-structuring results

ISM Level	Factors	Structural Interpretation
Level 1	B1, B2, B3, B4, B5, B6	World-class performance outcomes
Level 2	A5, A8	Transformation of analysis into action and operational optimization
Level 3	A4, A7	Analytical engines and resilient decision-making
Level 4	A6	Central knowledge platform
Level 5	A2, A3	Perception, sensing, and edge processing
Level 6	A1, A9	Communication, data, and security infrastructure

The results in Table 3 show that the level structure of the model is formed from bottom to top according to the logic of "infrastructure → perception and processing → knowledge → analysis → optimization → performance outcomes." The placement of A1 and A9 at Level 6 indicates that the real-time communication network and cyber–physical security are the most fundamental prerequisites of the model. Without stable connectivity and data/operations security, the entire data and decision flow in the architecture is disrupted. The placement of A2 and A3 at Level 5 shows that edge processing and smart sensors, after the establishment of communication and security infrastructure, are responsible for perception and data preprocessing. This level converts raw equipment and process data into data usable for analysis. At Level 4, A6—intelligent knowledge management—is positioned. This indicates that maintenance knowledge, operational experience, maintenance instructions, and historical data should be structured and made retrievable before advanced analytics. At Level 3, A4 and A7 are positioned. This level includes dynamic failure prediction and resilient supply chain and plays the role of analytical and decision-making engines. Failure prediction without parts, tools, and resource planning cannot lead to downtime reduction. Therefore, the positioning of these two components at the same level indicates that technical failure analysis and supply-related decision-making should be considered simultaneously. At Level 2, A5 and A8 are positioned. This level represents the transformation of analytical insight into operational action; that is, preventive quality control and intelligent continuous improvement convert analytical outputs into process correction, scrap reduction, and performance improvement. At Level 1, the six indicators B1 to B6 are positioned as the final outcomes of the model. Based on the final level structuring, the ISM model can be displayed in six levels. This model is not the final model of the study; rather, it shows the stage-based and prerequisite structure of the factors and, together with DEMATEL outputs, forms the basis for designing the final AI-WCTPM architecture.

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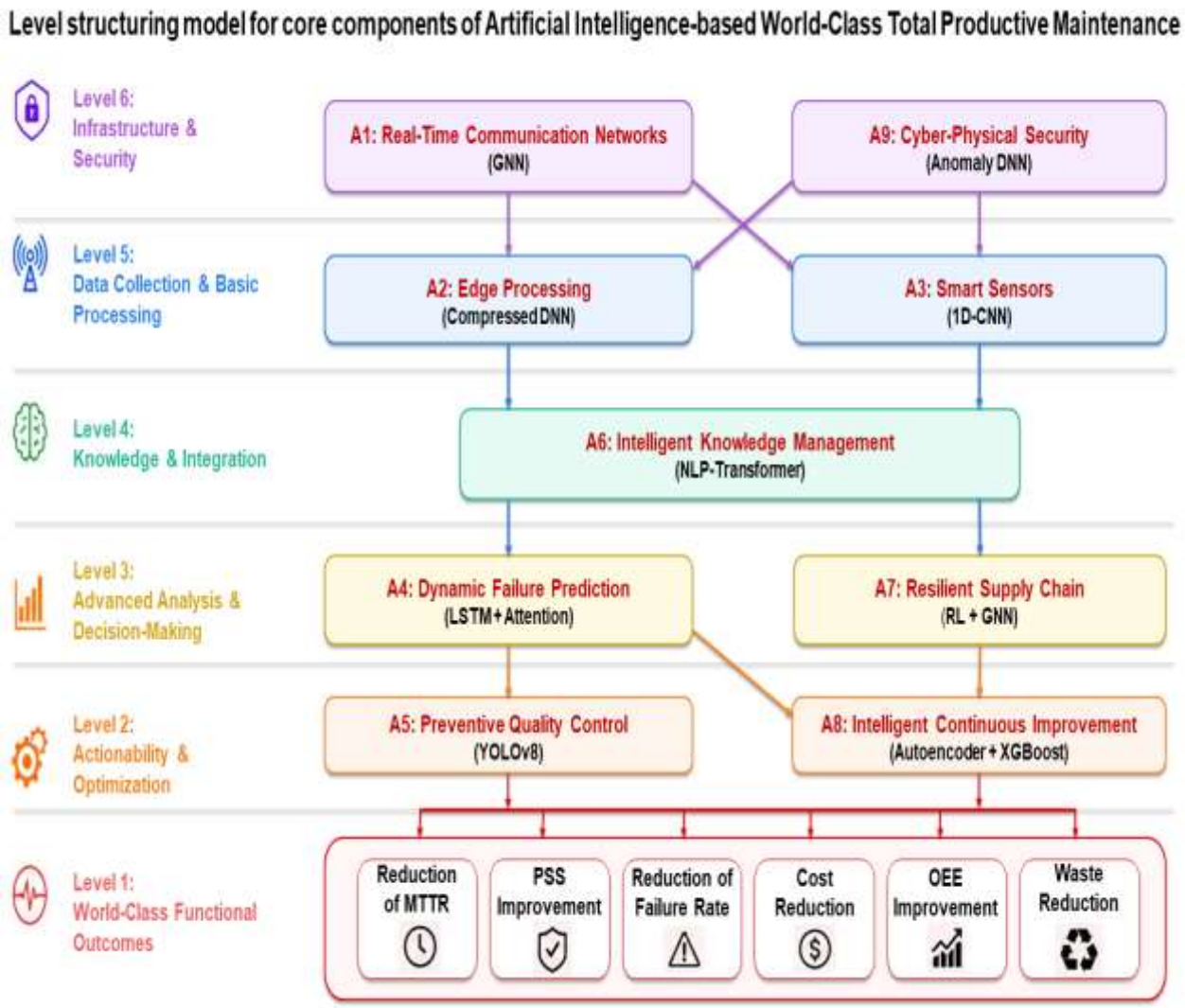


Figure 1. ISM level-structuring model for AI-based Total Productive Maintenance

Description of Figure 1: At the lowest level, A1 and A9 are positioned and act as foundational infrastructures. The next level includes A2 and A3, which receive and process data from the physical environment. Level 4 includes A6, which converts operational data and experience into usable knowledge. Level 3 includes A4 and A7, which are responsible for failure analysis and resilient decision-making. Level 2 includes A5 and A8, which convert analytical insight into corrective action, quality control, and continuous improvement. At the top of the model, B1 to B6 are positioned as world-class outcomes. From a managerial perspective, this structure shows that beginning implementation from Level 2 or Level 3 components without establishing Levels 6 and 5 carries a high risk. For example, implementing a dynamic failure-prediction model without a stable network, data security, reliable sensors, and edge processing will likely result in unstable or non-actionable outputs. Similarly, preventive quality control and intelligent continuous improvement will be effective only when analytical engines and the central knowledge platform provide reliable data and insight. To evaluate the stability of the ISM structure, the main threshold value was examined under two scenarios: a 5% decrease and a 5% increase. Evaluation criteria included the stability of the number of levels, stability of the position of infrastructural components, stability of the position of performance outcomes, and the absence of fundamental change in the overall logic of the model.

Table 4. Threshold sensitivity analysis results in the ISM structure

Analysis Scenario	Threshold Value	Structural Expectation	Interpretive Result
5% decrease in threshold	0.0418	Limited increase in relationships	The six-level structure was preserved, and the infrastructural–outcome logic did not fundamentally change
Main threshold	0.0440	Baseline structure	The six main levels of the model were extracted

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5% increase in threshold	0.0462	Limited removal of weak relationships	The main structure of the model was preserved, and B outcomes remained at the final level

The results of the sensitivity analysis show that the ISM structure is not dependent on a specific numerical threshold. Lowering the threshold allows some weaker relationships to enter the model, but does not change the overall logic. Increasing the threshold removes some marginal relationships, but the main positions of infrastructural components, analytical engines, and world-class outcomes remain stable. Therefore, the six-level model structure has acceptable stability and can serve, together with fuzzy DEMATEL outputs, as a basis for designing the final architecture.

In response to the third research question—how the final AI-WCTPM architecture can be derived by integrating the causal roles of components, ISM level structuring, corresponding AI tools, and structural/expert validation—the ISM levels were integrated with the causal roles and influence intensities derived from fuzzy DEMATEL and converted into executable architectural layers. After extracting the levels and controlling threshold stability, each ISM level was integrated with the causal role and influence intensity derived from fuzzy DEMATEL and converted into an architectural layer. Therefore, the final architecture is not merely a mechanical mapping of ISM levels. Rather, it results from the combination of three sources of information: the stage-based position of factors in ISM, the causal/dependent role and influence intensity in DEMATEL, and the artificial intelligence tools corresponding to the components. This mapping is presented in Table 5.

Table 5. Integrated mapping of DEMATEL and ISM into the architectural layers of the final AI-WCTPM model

ISM Level	Components	DEMATEL Role in Layer Interpretation	Architectural Layer Title	Core Function
Level 6	A1, A9	Enabling infrastructures for activating causal relationships	Communication, data, and security infrastructure	Real-time communication, data integration, and cyber–physical security of operations
Level 5	A2, A3	Support the influence intensity of analytical components through valid data	Edge processing and perception	Data collection, machine perception, preprocessing, and data structuring at the edge
Level 4	A6	Supports the conversion of data and experience into decision-making knowledge	Central knowledge platform	Converts experience, operational data, and maintenance reports into retrievable and usable knowledge
Level 3	A4, A7	Important causal levers in failure prediction and supply support	Advanced analytical engines	Failure prediction, trend analysis, and resilient supply-chain decision-making
Level 2	A5, A8	Causal levers close to action and performance improvement	Optimization engines	Preventive quality control and intelligent continuous improvement; conversion of insight into action
Level 1	B1 to B6	Outcomes affected by the causal and stage-based network	Performance monitoring platform	Monitoring and reporting of world-class performance indicators

The final AI-WCTPM architecture is based on the logic that data and decisions move within a continuous flow. In the first architectural layer, the real-time communication network and cyber–physical security provide the foundation for data and operational reliability. In the second layer, sensors and edge processing convert raw equipment, quality, and process data into analyzable data. In the third layer, intelligent knowledge management converts experiences, maintenance reports, and historical data into retrievable knowledge. In the fourth layer, dynamic failure prediction and resilient supply chain perform analysis and decision-making. In the fifth layer, preventive quality control and intelligent continuous improvement convert analytical outputs into corrective action. In the sixth layer, world-class indicators are monitored to evaluate the effect of the model on performance.

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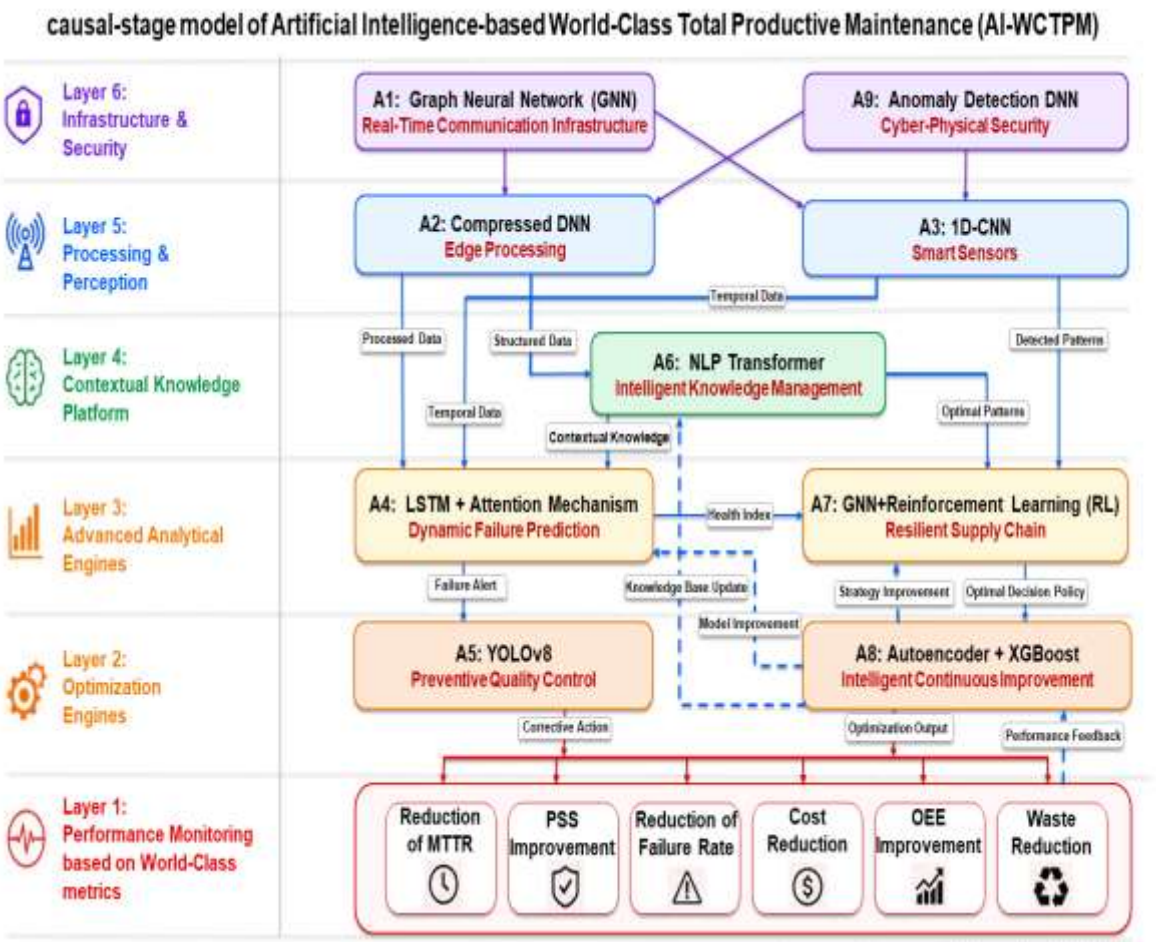


Figure 2. AI-WCTPM architecture based on integrating DEMATEL causal roles and ISM level structuring

Description of Figure 2: The architecture should be drawn in six layers from bottom to top. In the lowest layer, A1 and A9 should be placed; in the second layer, A2 and A3; in the third layer, A6; in the fourth layer, A4 and A7; in the fifth layer, A5 and A8; and in the top layer, B1 to B6. The main flow direction is from bottom to top. The intensity of relationships and causal roles of components derived from fuzzy DEMATEL can be displayed through arrow thickness or direction. A feedback loop should be drawn from the performance monitoring platform to the central knowledge platform and optimization engines to show the logic of learning and continuous improvement. After designing the final architecture, the model was evaluated by experts. The validation questionnaire of the final model included 16 items across six main dimensions: model comprehensiveness, logical and structural coherence, applicability in the Iranian automotive industry, adequacy of the artificial intelligence architecture, expected influence on world-class performance indicators, and overall model validity. The acceptance criteria for each item were a minimum mean of 3.5, standard deviation below 1, and CVI greater than 0.79.

Table 6. Expert validation results of the final model

Validation Indicator	Acceptance Criterion	Obtained Value	Result
Overall mean acceptance of the model	≥ 3.5	4.53	Strong approval
Mean standard deviation	< 1	0.44	Appropriate expert agreement
Overall Content Validity Index	≥ 0.79	0.93	Very desirable content adequacy

The combination of the three indicators shows that the final model is valid from the perspective of experts. The mean value of 4.53 indicates strong model acceptance, the standard deviation of 0.44 indicates convergence and appropriate agreement among experts, and the CVI value of 0.93 indicates high content adequacy of the model. Therefore, the AI-WCTPM causal–stage model is structurally, content-wise, and operationally defensible.

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4. Discussion and Conclusion

The present study sought to design a causal–stage model of Artificial Intelligence–Based World-Class Total Productive Maintenance (AI-WCTPM) for the Iranian automotive industry by integrating the causal relationships identified through fuzzy DEMATEL with the hierarchical implementation logic derived from Interpretive Structural Modeling. The findings revealed a six-level architecture in which real-time communication networks and cyber–physical security constituted the foundational infrastructure; edge processing and smart sensors formed the perception and data-processing layer; intelligent knowledge management occupied the central knowledge layer; dynamic failure prediction and resilient supply chain represented the advanced analytical and decision-making layer; preventive quality control and intelligent continuous improvement formed the optimization and action layer; and world-class performance indicators constituted the ultimate outcome layer. This structure demonstrates that AI-based maintenance transformation should not be understood as the adoption of isolated algorithms or stand-alone digital technologies. Rather, it is a cumulative and interdependent transformation process in which infrastructural, informational, analytical, and operational capabilities must be developed in a logical sequence before world-class performance can be achieved.

The positioning of real-time communication networks and cyber–physical security at the foundational level is one of the most important findings of the study. This result indicates that intelligent maintenance cannot operate reliably without stable connectivity, secure data transmission, interoperability among equipment and information systems, and protection of physical and digital assets. In other words, even highly accurate predictive models cannot generate sustainable organizational value when the underlying data infrastructure is fragmented, insecure, or unavailable in real time. This finding is consistent with research emphasizing that the digitalization of maintenance requires an enabling technological infrastructure capable of connecting equipment, people, and analytical systems within an integrated operational environment (Tortorella et al., 2024). It is also aligned with the argument that integration between TPM and Industry 4.0 depends on the establishment of standardized digital foundations rather than the fragmented adoption of advanced technologies (Mouhib et al., 2025). In the Iranian automotive context, this result is particularly meaningful because digital transformation has been shown to depend strongly on infrastructure readiness, information-system integration, and organizational preparedness (Mozaffari Mehr & Taghavi Fard, 2024). Similarly, Industry 4.0 implementation in the automotive sector requires coordinated technological and organizational development in order to contribute to sustainable industrial performance (Ardehi et al., 2023).

The next level of the model comprised edge processing and smart sensors, reflecting the importance of reliable data acquisition and local processing. This result confirms that artificial intelligence in maintenance begins with the capacity to observe the physical condition of equipment and manufacturing processes continuously and accurately. Smart sensors transform machine behavior, vibration, temperature, pressure, current, acoustic signals, and other operational phenomena into analyzable data, while edge-processing technologies reduce latency and enable rapid preliminary analysis near the equipment. Such a structure is consistent with recent edge–cloud industrial Internet of Things frameworks for predictive maintenance, which emphasize the complementary roles of local computation and higher-level analytics in manufacturing environments (Somu & Dasappa, 2025). The result is also supported by developments in high-speed data infrastructure for visual anomaly detection, where efficient transmission and processing are necessary to convert large volumes of industrial data into timely diagnostic information (Wang & Liang, 2025). Deep-learning-based predictive-maintenance architectures similarly demonstrate that the quality of analytical outputs depends substantially on the reliability, organization, and preprocessing of input data (Li et al., 2024). Thus, the placement of sensing and edge capabilities before advanced analytics is theoretically and operationally justified.

Intelligent knowledge management was positioned at the intermediate level of the model between data processing and advanced analytical capabilities. This finding suggests that maintenance data alone are insufficient for intelligent decision-making unless they are converted into structured, accessible, and reusable knowledge. Maintenance organizations generate large volumes of technical information through work orders, failure reports, maintenance histories, operator observations, manuals, corrective-action records, and accumulated technician experience. When such information remains unstructured, a considerable portion of organizational learning is lost. The current finding is supported by research showing that causal and technical knowledge can be extracted from extensive maintenance documents and transformed into machine-readable forms

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that support decision-making (Hershowitz et al., 2024). It is also consistent with data-driven maintenance research indicating that effective predictive maintenance depends on the integration of historical operational information with current condition data rather than on isolated algorithmic analysis (Giordano et al., 2022). Therefore, knowledge management serves as a bridge between physical data acquisition and higher-level intelligence, enabling the maintenance system to learn from both current signals and accumulated organizational experience.

At the fourth architectural layer, dynamic failure prediction and resilient supply chain were located together as advanced analytical and decision-making engines. The positioning of these two dimensions at the same level represents an important conceptual contribution of the study. Failure prediction alone cannot ensure maintenance effectiveness unless predicted failures can be linked to the timely availability of spare parts, tools, technical resources, and maintenance personnel. Conversely, supply-chain resilience cannot be optimized effectively without reliable information about equipment condition, expected failures, and intervention priorities. This interdependence extends predictive maintenance beyond the technical diagnosis of equipment and connects it to organizational resource allocation. Previous reviews confirm that predictive maintenance uses machine-learning models to forecast equipment degradation and support timely interventions, but its effectiveness depends on integrating analytical output with operational planning (Achouch et al., 2022; Hector & Panjanathan, 2024; Taoufyq et al., 2025). Data-driven digital twins also support this interpretation because they connect physical equipment states, predictive models, and operational decision-making in a continuous information loop (Khan et al., 2025). Furthermore, the application of graph neural networks and reinforcement learning to network optimization demonstrates the potential of AI to support adaptive decisions in complex supply systems (Wang et al., 2025). Consequently, the joint placement of failure prediction and resilient supply-chain management highlights the need to connect technical intelligence with logistical capability.

Preventive quality control and intelligent continuous improvement were positioned immediately below the final performance outcomes, indicating that analytical intelligence must ultimately be translated into operational action. This finding is especially relevant to automotive manufacturing, where deterioration in equipment condition can influence dimensional accuracy, process consistency, defect rates, rework, and scrap before a complete breakdown occurs. Predictive maintenance therefore creates greater organizational value when its outputs are integrated with quality management and process-improvement mechanisms. This result is strongly aligned with evidence showing that predictive-maintenance optimization can be improved by incorporating product-quality parameters into machine-learning models and maintenance decisions (Riccio et al., 2024). Intelligent manufacturing systems designed for predictive maintenance similarly demonstrate that analytical models should be incorporated into practical decision processes rather than evaluated solely in terms of prediction accuracy (Cinar et al., 2022). In this regard, intelligent continuous improvement represents the learning mechanism of the architecture, because the outcomes of corrective actions can be returned to the knowledge and analytical layers to improve future predictions and decisions.

The final level consisted of six world-class performance outcomes: reduction in mean time to repair, improvement in service availability, reduction in failure rate, reduction in maintenance costs, improvement in Overall Equipment Effectiveness, and reduction in production scrap. Their placement at the top of the structure confirms that world-class maintenance outcomes should be interpreted as dependent consequences of an integrated system rather than direct effects of technology acquisition. This is consistent with the strategic view of maintenance management, according to which maintenance contributes to organizational performance only when it is aligned with production, quality, cost, and business objectives (Tsang, 2002). It also supports the established relationship between TPM and world-class manufacturing, where maintenance contributes to productivity, reliability, quality, waste reduction, and competitive manufacturing capability (Farsijani et al., 2012). Performance evaluation in world-class systems similarly requires multidimensional indicators that connect operational practices to broader outcomes of efficiency, quality, and competitiveness (Farsijani & Dehghan, 2016). Moreover, maturity-based World-Class Manufacturing evaluation emphasizes that superior performance emerges through progressive capability development rather than through isolated improvement activities (de Andrade et al., 2021). The present study therefore extends these perspectives by showing how AI-based capabilities can be structurally organized to support such outcomes.

An important methodological finding concerns the distinction between causal influence and implementation sequence. The DEMATEL results underlying the present model indicated that some components, particularly dynamic failure prediction, preventive quality control, resilient supply chain, and intelligent continuous improvement, possess strong causal leverage,

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whereas the ISM results placed communication, security, sensing, and edge processing at deeper foundational levels. This distinction means that the most influential factor is not necessarily the first factor that should be implemented. High-leverage analytical capabilities may produce substantial performance effects, but their implementation depends on less visible enabling infrastructures. This finding supports the use of DEMATEL as a method for distinguishing influential and dependent relationships while also demonstrating why DEMATEL should be complemented by a hierarchical method. Methodological research has emphasized that appropriate threshold determination is critical for identifying meaningful relationships in DEMATEL-based structural analysis (Ebrahimi, 2023). Applications of DEMATEL in complex decision environments similarly demonstrate its value in revealing the relative influence and interconnectedness of multiple criteria (Nyimbili et al., 2023). The integration of DEMATEL with ISM therefore provides a more managerially interpretable model because causal strength is converted into a stage-based implementation structure.

The use of the median threshold and subsequent sensitivity analysis further strengthened the structural credibility of the proposed model. The results indicated that moderate decreases or increases in the threshold did not fundamentally alter the six-level architecture, the position of infrastructural elements, or the placement of world-class outcomes. This suggests that the model is not merely a consequence of a single arbitrary cut-off value. Such robustness is particularly important when converting continuous causal relationships into binary structural matrices, because overly low thresholds may generate excessively dense networks, whereas overly high thresholds may eliminate meaningful relationships. The selected approach is consistent with methodological efforts to establish defensible threshold values in DEMATEL analysis (Ebrahimi, 2023). The integration of causal analysis with hierarchical structuring is also in line with recent applications of combined DEMATEL–ISM approaches that transform complex causal networks into interpretable multi-level structures for managerial decision-making (Li et al., 2025).

The findings also reinforce the conceptual importance of evaluating AI-WCTPM as an integrated organizational system rather than as a portfolio of technological tools. Previous studies have frequently focused on predictive models, machine-learning techniques, anomaly detection, or specific digital technologies. Although these contributions are essential, their isolated implementation cannot guarantee world-class maintenance performance. The present model instead suggests a continuous data–knowledge–decision–action–performance cycle. Data are generated and transmitted through the infrastructural and sensing layers, transformed into knowledge through intelligent knowledge management, analyzed through predictive and resilient decision mechanisms, converted into operational improvements through quality control and continuous improvement, and finally assessed through world-class performance indicators. The doctoral research on which the present model builds similarly emphasized the need to connect AI capabilities with World-Class TPM rather than treating them as independent digital initiatives (Mohammadi Rad et al., 2026). The current study advances this logic by transforming identified causal relationships into an explicit stage-based architecture.

Finally, expert validation provided additional support for the practical and conceptual adequacy of the proposed model. The overall mean acceptance of 4.53, standard deviation of 0.44, and Content Validity Index of 0.93 indicate a high degree of expert agreement concerning the comprehensiveness, logical coherence, applicability, AI architecture, expected performance effects, and overall validity of the model. Taken together with the threshold-sensitivity findings, these results suggest that the proposed six-stage AI-WCTPM architecture offers a defensible framework for guiding the transformation of maintenance in the Iranian automotive industry. Its principal contribution is not the introduction of any single artificial intelligence technique, but the specification of how technological and managerial capabilities should be causally integrated and sequentially implemented to create sustainable improvements in world-class maintenance performance.

The present study has several limitations that should be considered when interpreting its findings. First, the model was developed specifically for the Iranian automotive industry, and the infrastructural, technological, organizational, and regulatory characteristics of this setting may limit direct generalization to other industries or countries. Second, the stage structure was derived from expert judgments and previously validated DEMATEL relationships rather than longitudinal implementation data collected from operating production lines. Third, although threshold-sensitivity analysis demonstrated acceptable structural stability, different analytical criteria or alternative structural-modeling techniques might produce variations in the positioning of some components. Fourth, expert validation assessed the perceived comprehensiveness, coherence, applicability, and content adequacy of the model, but it did not constitute an empirical test of the model's actual effects on downtime, failure rates, OEE,

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maintenance costs, or scrap. Finally, the proposed architecture identifies corresponding AI technologies at a conceptual level, whereas differences in equipment age, data quality, information-system maturity, workforce competencies, and investment capacity across automotive firms may affect the feasibility and effectiveness of individual technologies.

Future studies should empirically test the proposed AI-WCTPM architecture using real-time production and maintenance data from automotive manufacturing plants. Longitudinal studies could examine whether implementation of the proposed layers in the specified sequence actually produces improvements in MTTR, availability, failure rate, maintenance cost, OEE, and scrap. Comparative research across automotive companies, industrial sectors, and countries could determine the extent to which the six-level architecture is generalizable or requires contextual adaptation. Future researchers could also develop an AI-WCTPM maturity index to evaluate the readiness of organizations at each architectural layer and identify investment priorities. Structural equation modeling, system dynamics, simulation, digital-twin experimentation, or longitudinal causal modeling could be used to test interactions among layers. Further studies could investigate human and organizational dimensions such as employee acceptance, digital skills, leadership support, data governance, organizational learning, and resistance to AI-enabled maintenance. Finally, future research could examine the economic feasibility of the model by comparing the investment requirements, implementation risks, and expected returns associated with alternative pathways for introducing the proposed capabilities.

Automotive manufacturers should implement AI-based maintenance as a staged transformation program rather than purchasing isolated predictive-maintenance applications. Managers should first assess the maturity of industrial communication networks, data availability, system interoperability, and cyber–physical security and address critical deficiencies before investing heavily in advanced analytical models. Smart sensing and edge-processing capabilities should then be established on critical assets and production lines, accompanied by standardized procedures for collecting, cleaning, labeling, and storing maintenance data. Organizations should create an integrated knowledge-management platform that combines maintenance records, technician experience, equipment documentation, failure histories, and corrective actions. Predictive-maintenance capabilities should subsequently be connected with spare-parts planning and supply-chain decisions so that predicted failures can trigger executable interventions. Preventive quality control and intelligent continuous-improvement mechanisms should translate analytical outputs into process corrections and organizational learning. Implementation should preferably begin with a high-impact pilot production line, with baseline values established for MTTR, availability, failure rate, maintenance cost, OEE, and scrap. Clear executive responsibility should be assigned to each architectural layer, while maintenance, production, quality, information technology, automation, data-analysis, and supply-chain units should participate jointly in implementation and performance monitoring.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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