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Identification and Causal Analysis of Artificial Intelligence Capabilities for Advancing Total Productive Maintenance toward World-Class Standards in the Automotive Industry

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Abstract

In the era of Industry 5.0, transforming Total Productive Maintenance (TPM) in the automotive industry requires moving beyond reactive and experience-based maintenance toward a data-driven, predictive, and artificial intelligence-based system. Although research on intelligent maintenance has expanded considerably, much of the existing literature focuses on isolated algorithms, prediction accuracy, or narrow technological applications, while insufficient attention has been paid to identifying which AI capabilities are valid for enabling World-Class TPM and how they operate within a causal influence network. This study aims to identify, validate, and causally analyze artificial intelligence capabilities for World-Class TPM in the automotive industry. First, initial capabilities were extracted through thematic analysis of expert data. A single-round fuzzy Delphi method, was then applied to screen and stabilize the core capabilities, while expert consensus was controlled through fuzzy distance, consensus percentage, and alpha-cut criteria. The AI tools corresponding to the selected capabilities were conceptually validated based on the literature. Finally, fuzzy DEMATEL was used to analyze the intensity and direction of causal relationships. The findings show that 9 out of 20 initial capabilities were stabilized as core AI capabilities. Dynamic failure prediction, preventive quality control, resilient supply chain, and intelligent continuous improvement emerged as the strongest causal and leverage capabilities. The study contributes by providing a validated and causally analyzed set of AI capabilities that can support managerial decision-making for prioritizing World-Class TPM investments in the automotive industry.

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

1. Introduction

The automotive industry operates within one of the most demanding manufacturing environments, where high production volumes, complex assembly systems, extensive supplier networks, strict quality requirements, capital-intensive equipment, and strong interdependence among production stages make operational reliability a strategic necessity. A disruption in a single machine, production cell, or supporting system can propagate throughout the manufacturing process and generate downtime, production losses, quality defects, excess scrap, delayed deliveries, and rising maintenance costs. Under these conditions, maintenance can no longer be regarded merely as a technical support function concerned with repairing equipment after failure.

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Instead, it has become an integral component of manufacturing competitiveness, operational continuity, productivity, product quality, and long-term organizational performance. Total Productive Maintenance (TPM) has emerged as one of the major managerial and operational approaches through which organizations seek to increase equipment effectiveness, reduce losses, encourage employee participation, institutionalize preventive practices, and integrate maintenance activities with production objectives. Previous research has shown that the contribution of TPM to world-class manufacturing extends beyond equipment repair and encompasses broader improvements in productivity, group technology, equipment utilization, and manufacturing capability (Farsijani et al., 2012). Likewise, performance evaluation aimed at achieving world-class products requires systematic attention to competitiveness, responsiveness, quality, efficiency, and value creation rather than relying exclusively on traditional production measures (Farsijani & Dehghan, 2016).

The growing complexity of modern manufacturing, however, has exposed important limitations in conventional maintenance systems. Traditional preventive maintenance generally relies on predetermined service intervals, historical experience, standardized schedules, and technician judgment, while reactive maintenance intervenes only after equipment degradation has already resulted in malfunction or failure. Although these approaches remain necessary in particular operational contexts, they are increasingly insufficient for production systems characterized by continuous data generation, variable operating conditions, interconnected equipment, and rapidly changing production requirements. Within contemporary TPM systems, the use of well-defined key performance indicators is essential for linking maintenance activities to organizational performance, particularly through measures such as Overall Equipment Effectiveness, failure rates, repair time, maintenance costs, and quality losses (Toke & Kalpande, 2023). At the same time, the emergence of Industry 4.0 has created opportunities to transform TPM from a predominantly schedule-based and experience-driven system into a data-driven, predictive, adaptive, and intelligent maintenance architecture. Recent attempts to integrate TPM with Industry 4.0 indicate that digital technologies can strengthen conventional TPM principles when data acquisition, analytics, automation, connectivity, and intelligent decision support are systematically embedded within maintenance practices (Mouhib et al., 2025).

Artificial intelligence (AI) is increasingly central to this transformation because it provides analytical mechanisms for converting large volumes of heterogeneous industrial data into meaningful predictions, classifications, alerts, decisions, and improvement actions. Manufacturing systems now generate continuous streams of information from sensors, machines, programmable logic controllers, manufacturing execution systems, inspection platforms, maintenance records, enterprise systems, and supply-chain networks. AI techniques can analyze these data to identify patterns that would be difficult to detect through traditional analytical procedures. In predictive maintenance specifically, machine learning and deep learning techniques are increasingly used for condition monitoring, fault diagnosis, anomaly detection, remaining useful life estimation, failure forecasting, and maintenance scheduling. Reviews of predictive maintenance research demonstrate that contemporary approaches increasingly combine data-driven modeling with advanced sensing, machine learning, and intelligent planning in order to anticipate failures before they disrupt operations (Hector & Panjanathan, 2024). Systematic reviews similarly indicate that predictive maintenance is moving toward increasingly sophisticated architectures capable of integrating historical data, real-time operating conditions, degradation patterns, and decision-support mechanisms (Taoufyq et al., 2025).

Deep learning has further expanded the analytical capacity of predictive maintenance by enabling automated feature extraction from high-dimensional and nonlinear equipment data. Architectures involving convolutional neural networks, recurrent neural networks, autoencoders, attention mechanisms, and other deep models have demonstrated particular relevance where conventional statistical techniques have difficulty capturing complex degradation behavior (Li et al., 2024). In vehicle and automotive maintenance contexts, AI-driven fault diagnosis also offers a pathway toward earlier identification of malfunction, improved diagnostic precision, reduced inspection time, and more informed maintenance intervention (Hossain et al., 2024). Recent reviews of AI-driven predictive maintenance in vehicles emphasize that intelligent maintenance depends not only on the accuracy of algorithms but also on the availability of reliable sensors, suitable data architectures, continuous monitoring, interpretable outputs, and practical integration with maintenance workflows (Mahale et al., 2025). Accordingly, the strategic value of AI in TPM emerges when intelligent models are embedded into a broader capability system connecting equipment data, human knowledge, production requirements, quality control, maintenance planning, and organizational decision-making.

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The effectiveness of such systems begins with the quality and timeliness of industrial data. Smart sensors can continuously capture vibration, temperature, pressure, acoustic, electrical, mechanical, and operational signals that reflect the condition of equipment and production processes. AI-based monitoring can then identify abnormal behavior before deterioration becomes a critical failure. The importance of combining artificial intelligence with product-quality monitoring and predictive maintenance has been highlighted in Industry 4.0 research, where intelligent sensing and analytics support both equipment health monitoring and quality assurance (Andrianandrianina Johanesa et al., 2024). Yet high-volume industrial sensing also creates challenges associated with data-transfer latency, computing demands, and real-time response. Advanced data infrastructures and edge-oriented architectures are therefore becoming increasingly important for enabling rapid anomaly detection and decision-making close to the source of industrial data. Research on accelerated visual anomaly detection demonstrates that high-speed data infrastructure can substantially strengthen real-time intelligent manufacturing applications where delays in data communication may reduce the practical value of AI outputs (Wang & Liang, 2025).

AI-enabled TPM must also extend beyond failure prediction to the prevention of quality losses. In automotive manufacturing, deterioration in equipment condition frequently manifests not only as complete machine failure but also as subtle deviations in welding, assembly, painting, surface finishing, dimensional accuracy, sealing, or component quality. Consequently, the boundary between maintenance management and quality management is becoming increasingly permeable. AI-enabled visual inspection can detect defects at an early stage and thereby provide signals about both product nonconformity and underlying process or equipment instability. Recent systemic evidence concerning AI applications for automotive quality defects indicates that machine vision and intelligent inspection technologies have significant potential to improve defect detection, reduce inspection variability, and support movement toward zero-defect manufacturing (Morales Matamoros et al., 2025). Trustworthy deep vision frameworks such as YOLO-based architectures further demonstrate the potential for automated industrial defect detection while drawing attention to the need for reliability and security in AI-based inspection systems (Liang & Chen, 2025). Preventive quality control can therefore be conceptualized as an important AI capability within advanced TPM because it links equipment performance directly to the prevention of rework, scrap, and production instability.

Another critical dimension concerns the conversion of maintenance data into organizational knowledge. Manufacturing organizations accumulate extensive repositories of maintenance reports, failure descriptions, work orders, equipment manuals, corrective-action documents, technicians' notes, and historical troubleshooting experiences. Much of this information remains stored in unstructured textual form and is consequently difficult to retrieve, integrate, and reuse systematically. Natural language processing and transformer-based approaches create opportunities to extract relationships, maintenance actions, causal mechanisms, and technical knowledge from these records. Research on causal knowledge extraction from long maintenance documents demonstrates that AI can transform unstructured maintenance information into structured knowledge capable of supporting diagnosis and decision-making (Hershowitz et al., 2024). Similarly, the decomposition of maintenance actions through natural language processing illustrates how textual maintenance information can be converted into task-level knowledge that can assist planning, standardization, and operational learning in automotive environments (Giordano & Fantoni, 2025). Intelligent knowledge management is therefore essential if AI-enabled TPM is to institutionalize learning rather than repeatedly depend on fragmented individual experience.

The maintenance system is also embedded within a larger production and supply-chain ecosystem. Equipment availability depends not only on accurate diagnosis but also on the timely availability of spare parts, supplier reliability, logistics coordination, inventory decisions, and routing. In interconnected manufacturing networks, maintenance disruptions may be amplified when required components are unavailable or when inventory and logistics systems are unable to react to changing operational conditions. Graph-based machine learning provides a potentially powerful mechanism for representing these interconnected structures because machines, suppliers, warehouses, maintenance stations, and transportation links can be modeled as relational networks. Research integrating graph neural networks with multi-agent reinforcement learning has demonstrated the value of such approaches for adaptive inventory-control problems in complex supply chains (Kotecha & del Rio-Chanona, 2025). Reinforcement learning combined with graph neural networks and attention mechanisms has likewise been used to optimize supply-chain routing decisions in dynamic network environments (Wang et al., 2025). These developments suggest that resilient supply-chain capability should be incorporated into the conceptualization of AI-enabled

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TPM, particularly in automotive manufacturing where production continuity depends strongly on synchronized parts and maintenance resources.

Digital twins represent another major development in the transition toward intelligent maintenance. By integrating physical assets with continuously updated digital representations, digital twins can support equipment-state monitoring, scenario evaluation, failure prediction, and maintenance decision-making. Data-driven digital-twin frameworks have been proposed as mechanisms for integrating smart manufacturing data with predictive maintenance functions, thereby enabling more dynamic assessment of system health and availability (Khan et al., 2025). Such architectures are especially relevant to world-class maintenance because they move decision-making from static reporting toward continuously updated operational intelligence. Nevertheless, the adoption of highly interconnected digital architectures introduces additional vulnerabilities. Cyber–physical maintenance systems rely on trustworthy sensor signals, secure communication channels, and reliable data processing. Manipulated or anomalous industrial data may generate incorrect maintenance recommendations, false failure alarms, or unsafe operational decisions. Deep learning approaches to cyber-threat hunting in industrial Internet of Things environments therefore demonstrate that intelligent cybersecurity must accompany the expansion of AI-based manufacturing systems (Yazdinejad et al., 2023). Cyber–physical security should consequently be considered an enabling capability rather than a peripheral technical concern.

The value of AI also lies in its capacity to support continuous improvement. TPM has historically emphasized systematic elimination of losses and the continuous enhancement of equipment effectiveness. In intelligent manufacturing environments, these principles can be strengthened by learning algorithms that detect recurring patterns, classify performance states, prioritize corrective actions, and update decisions as new data become available. Data-driven frameworks for TPM show that maintenance analytics can support more systematic identification of losses and improve the alignment of maintenance decisions with performance objectives (Lucantoni et al., 2025). This transition is important because World-Class TPM should not be understood as the simple adoption of individual digital tools. Rather, it requires a coherent configuration of complementary capabilities through which sensing, connectivity, analytics, quality control, learning, knowledge, security, and supply-chain coordination jointly improve maintenance and manufacturing outcomes.

This challenge is particularly salient in the Iranian automotive industry. Digital transformation in automotive manufacturing is shaped not only by technological availability but also by organizational readiness, infrastructure, data integration, managerial capability, and the capacity to redesign established production processes. Research concerning digital transformation based on the Fourth Industrial Revolution in Iran Khodro has emphasized the need for an integrated transformation architecture rather than isolated technological interventions (Mozaffari Mehr & Taghavi Fard, 2024). Similarly, research on Industry 4.0 implementation for achieving sustainable development goals in Iran Khodro indicates that technological transformation must be supported by infrastructural, organizational, operational, and strategic conditions if it is to generate sustainable results (Ardehi et al., 2023). These findings imply that AI adoption in maintenance should be addressed as a capability-development problem rather than merely as a technology-acquisition decision.

Despite the rapid expansion of research on AI, predictive maintenance, intelligent quality control, digital twins, supply-chain analytics, and smart manufacturing, an important conceptual and managerial gap remains. Much of the existing literature examines particular algorithms, technologies, or applications independently. Such research is essential for demonstrating technical feasibility, but it does not necessarily identify which AI capabilities should be prioritized when the objective is to transform TPM toward world-class standards. An organization may have access to numerous technological alternatives yet still lack a defensible basis for determining which capabilities are foundational, which are enabling, which exert influence on other capabilities, and which primarily represent downstream outcomes. The managerial problem is therefore not simply whether AI can improve maintenance, but how a coherent portfolio of AI capabilities should be identified, validated, structured, and prioritized.

Addressing this problem also requires methods capable of dealing with interdependence and uncertainty. AI capabilities within TPM are unlikely to operate independently; for example, predictive maintenance may depend on sensing and edge processing, while continuous improvement may depend on predictive outputs, quality information, and organizational knowledge. Decision-making methods that only rank factors without examining causal relationships may therefore provide an incomplete representation of the system. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method is

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particularly suitable for analyzing complex influence structures by distinguishing causal factors from dependent factors and assessing both direct and indirect relationships. Fuzzy DEMATEL extends this logic by representing ambiguity in expert judgments, making it appropriate for strategic and technological problems where precise quantitative relationships are unavailable (Govindan et al., 2015). DEMATEL has been successfully adapted to multi-criteria problems requiring identification of causal structure and influential dimensions under uncertain evaluation conditions (Nyimbili et al., 2023). Recent integrated applications combining DEMATEL with complementary structural and probabilistic methods further demonstrate the usefulness of causal mapping for revealing the interdependence, hierarchy, and strategic importance of complex system factors (Li et al., 2025).

A methodological issue within DEMATEL also concerns the identification of meaningful influence thresholds, because an excessively low threshold can create an unreadably dense causal network whereas an excessively high threshold may eliminate substantively important relationships. Research addressing threshold identification in DEMATEL has shown that threshold selection should be analytically justified rather than treated as an arbitrary graphical decision (Ebrahimi, 2023). This consideration becomes particularly important when AI capabilities are being evaluated for managerial prioritization, because decision-makers require a causal structure that is sufficiently parsimonious to interpret while still preserving strategically significant relationships. Combining expert knowledge, validation procedures, fuzzy evaluation, and causal analysis can therefore provide a more rigorous approach to identifying those AI capabilities that possess the greatest leverage for improving world-class maintenance outcomes.

Taken together, the literature indicates substantial progress in intelligent sensing, predictive maintenance, quality inspection, digital twins, maintenance knowledge extraction, supply-chain optimization, cybersecurity, and data-driven TPM; however, these streams remain comparatively fragmented and have not sufficiently converged into an empirically validated capability architecture for World-Class TPM in the automotive industry. The central research need is therefore to move beyond isolated technological applications toward a systemic understanding of AI capabilities as mutually connected organizational and technological mechanisms that influence maintenance performance, equipment effectiveness, quality, reliability, cost, availability, and production stability. Such an approach can provide automotive managers with a stronger basis for allocating resources, sequencing digital investments, strengthening maintenance infrastructure, and identifying the capabilities that exert the greatest causal leverage over world-class performance.

Accordingly, the aim of this study is to identify, validate, and causally analyze the core artificial intelligence capabilities required to advance Total Productive Maintenance toward World-Class standards in the automotive industry.

2. Methods and Materials

This study is applied-developmental in terms of purpose and exploratory-causal and expert-based in terms of strategy. Its objective is to identify, validate, and causally analyze AI capabilities for World-Class TPM in the automotive industry. Since the research problem lies at the intersection of TPM, world-class manufacturing, artificial intelligence, and the automotive industry, broad and structured field data were not available for all capabilities. Therefore, the research logic was based on the systematic transformation of expert knowledge into a validated and causally analyzed set of capabilities.

The research process was designed in six steps. First, expert data were analyzed using thematic analysis and the initial capabilities were extracted. Second, the content validity of the capabilities was evaluated using the Content Validity Ratio and Content Validity Index. Third, a single-round fuzzy Delphi method was applied to screen the capabilities and stabilize the core capabilities. Fourth, fuzzy data were defuzzified using the Converting Fuzzy Data into Crisp Scores method, and expert consensus was controlled using fuzzy distance, consensus percentage, and alpha-cut criteria. Fifth, the AI tools corresponding to the selected capabilities were conceptually validated against the existing literature. Sixth, fuzzy DEMATEL was applied to analyze causal relationships, influence intensity, and the network role of the capabilities.

The expert panel included specialists from the automotive industry in the fields of maintenance, production, quality, information technology and data, artificial intelligence, and supply chain. Experts were selected purposively to cover the technical, managerial, data-related, quality-related, and supply-related dimensions of the problem. The selection criteria included relevant experience in the automotive industry, familiarity with real failure and downtime problems, knowledge of

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TPM, familiarity with world-class performance requirements, the ability to judge the operational feasibility of capabilities, and a general understanding of data and AI technologies.

Ten experts from Iran Khodro and SAIPA, both located in Tehran, were included. Their composition was designed so that capability evaluation would not be conducted merely from a technological perspective, but would also reflect production, maintenance, quality, data, security, supply, and implementation dimensions.

Four instruments were used for data collection. The first instrument was a semi-structured expert questionnaire designed to extract initial capabilities, identify the requirements of AI-based maintenance, and understand the gap between the current situation and world-class performance. The second instrument was a content-validation form used to assess the necessity and relevance of the extracted capabilities. The third instrument was a single-round fuzzy Delphi questionnaire in which experts provided minimum, most likely, and maximum values for each capability on a 0–10 scale. The fourth instrument was a fuzzy DEMATEL questionnaire used to measure the intensity of the influence of each capability on other capabilities and performance outcomes.

In the first step, the data obtained from the semi-structured questionnaire were analyzed and the experts' statements about the requirements of AI-based World-Class TPM were coded. Similar codes were then organized into sub-themes and main themes. The output of this stage was an initial list of capabilities and world-class outcome indicators. The purpose of this step was to convert qualitative expert data into a set of items suitable for quantitative evaluation in subsequent stages. Because of the journal-oriented nature of the article, the complete list of initial codes and themes is not reported in the main text and is more suitable for an appendix.

After extracting the initial capabilities, their content validity was examined at two levels: necessity and relevance. The Content Validity Ratio was used to measure the necessity of each capability. This index is calculated based on the number of experts who consider an item essential and is commonly used in expert-based research to retain or remove items (Lawshe, 1975). The CVR formula is as follows:

$$CVR = (Ne - N/2) / (N/2) \quad (1)$$

In this formula, Ne is the number of experts who evaluated the capability as essential, and N is the total number of experts.

The Content Validity Index was used to evaluate the relevance and appropriateness of each capability to the research construct. This index indicates the proportion of experts who evaluated an item as acceptable in terms of relevance (Polit & Beck, 2006). The I-CVI formula is as follows:

$$I\text{-}CVI = Na / N \quad (2)$$

In this formula, Na is the number of experts who evaluated the capability as acceptable in terms of relevance and appropriateness, and N is the total number of experts. In addition, the S-CVI/Ave was calculated to assess the overall quality of the instrument. Given the number of experts, the critical value of CVR was set at 0.62 and the acceptable value of I-CVI was set at 0.80.

After content validation, a single-round fuzzy Delphi method was used to screen and stabilize the core capabilities. Fuzzy Delphi is appropriate for problems in which expert judgments involve ambiguity, uncertainty, and linguistic evaluation, and these judgments need to be converted into analyzable values (Ishikawa et al., 1993). In this study, each expert provided three values for each capability: minimum, most likely, and maximum on a 0–10 scale. These three values formed a triangular fuzzy number for each judgment.

The triangular fuzzy number of each assessment was defined as follows:

$$\tilde{A}ij = (lij, mij, uij) \quad (3)$$

In this formula, lij is the minimum value, mij is the most likely value, and uij is the maximum value assigned by expert j to capability i. Triangular fuzzy numbers were used because they can represent linguistic and approximate expert judgments in a simple and calculable format (Kaufmann & Gupta, 1988).

To aggregate expert judgments, the component-wise mean of fuzzy numbers was calculated:

$$\tilde{A}i = (li, mi, ui) \quad (4)$$

In this expression, li, mi, and ui represent the mean values of the minimum, most likely, and maximum scores for capability i, respectively. Based on expert consensus, the acceptance threshold for a capability in the fuzzy Delphi stage was a crisp score equal to or greater than 8. Capabilities reaching this threshold after defuzzification were accepted as core AI capabilities for World-Class TPM.

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To convert the aggregated fuzzy numbers into comparable crisp values, the Converting Fuzzy Data into Crisp Scores method was applied. This method enables the conversion of fuzzy data into crisp values in multi-criteria decision-making problems and is suitable for comparing alternatives after aggregating fuzzy judgments (Opricovic & Tzeng, 2003). After defuzzification, the crisp value of each capability was compared with the acceptance threshold of 8.

To ensure that the acceptance of capabilities was not based solely on crisp scores, expert consensus was also controlled. Three criteria were used for this purpose: fuzzy distance, expert consensus percentage, and alpha-cut. A fuzzy distance below 0.20, a consensus percentage of at least 75%, and an alpha-cut of at least 0.50 were considered as consensus-acceptance criteria. Capabilities that passed both the crisp-score threshold and the consensus criteria entered the fuzzy DEMATEL stage.

After stabilizing the selected capabilities, the AI tools corresponding to each capability were conceptually validated based on the literature. The purpose of this stage was to ensure consistency among the nature of the problem, data type, managerial-operational function of the capability, and the proposed AI tool. This stage complemented fuzzy Delphi because Delphi identifies which capabilities are accepted by experts, whereas conceptual validation shows whether the AI tool assigned to each capability is defensible in the specialized literature.

Fuzzy DEMATEL was used to analyze causal relationships among the selected capabilities and world-class outcome indicators. DEMATEL is designed to analyze the direction and intensity of influence among factors in complex systems and makes it possible to distinguish influential and dependent factors through indices such as D, R, D+R, and D−R (Gabus & Fontela, 1972). In this study, because of the ambiguity in expert judgments and the linguistic nature of influence assessments, fuzzy DEMATEL was applied. Fuzzy DEMATEL is suitable for causal analysis under uncertainty and expert-based judgment conditions (Govindan et al., 2015).

In this stage, the core capabilities were coded as A1 to A9 and the world-class outcome indicators were coded as B1 to B6. For each expert, a fuzzy direct-relation matrix was formed. In this matrix, the intensity of the influence of factor i on factor j was evaluated using a fuzzy linguistic scale. The fuzzy direct-relation matrices were then aggregated using the component-wise mean, and the collective fuzzy direct-relation matrix was obtained. After normalization, the fuzzy total-relation matrix was calculated. This matrix represented both direct and indirect relationships among factors in fuzzy form.

The fuzzy total-relation matrix was then defuzzified using the CFCS method, and the output of this stage was the crisp total-relation matrix T. Therefore, in this study, matrix T refers to the final crisp total-relation matrix obtained after defuzzifying the fuzzy total-relation matrix. After obtaining matrix T, influence, dependence, prominence, and causality indices were calculated. The D index was obtained from the row sums of matrix T, while the R index was obtained from the column sums of matrix T. The D+R index indicates the prominence or overall importance of a factor in the influence network, whereas the D−R index indicates the causal or dependent role of a factor. A positive D−R value indicates a causal role, while a negative value indicates a dependent role.

Because DEMATEL results depend on expert judgments and perceived relationships among capabilities, the stability of the results was examined through perturbation analysis. In this analysis, the permissible elements of the crisp total-relation matrix T were retested under 5%, 10%, and 15% perturbation levels. For each perturbation level, 100 independent iterations were conducted, and the mean results were considered as the final output of that level. The stability criteria included changes in D+R prominence, changes in the dependence of B outcomes, ranking stability using Spearman's coefficient, and stability of causal/dependent roles based on the sign of D−R. Spearman's coefficient is suitable for evaluating ranking stability in multivariate analyses and for comparing rank orderings (Hair et al., 2019).

To draw the DEMATEL causal diagram, weak relationships had to be removed and more meaningful relationships retained. Therefore, four statistical criteria were examined for threshold determination: mean, median, mean minus standard deviation, and mean plus standard deviation. This comparison was conducted internally based on the non-zero off-diagonal elements of matrix T. The logic of selecting the threshold was that it should not be so restrictive that important relationships are removed, nor so permissive that the causal diagram becomes excessively dense and difficult to interpret. Finally, the median of the non-zero off-diagonal elements of matrix T was selected as the threshold because it was more robust to outliers and provided a better balance between preserving major relationships and reducing network density. The final threshold value was calculated as 0.044, and only relationships with tij values equal to or greater than this value were displayed in the DEMATEL diagram.

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3. Findings and Results

The thematic analysis of expert data, in response to the first research question, led to the identification of 20 initial capabilities and 6 world-class outcome indicators. To avoid turning the text into a raw reporting document, the complete list of 20 initial capabilities is not presented, and their refinement path is reported through content validity, fuzzy Delphi, and causal analysis. The world-class outcome indicators were selected based on the literature on TPM, world-class manufacturing, and data-driven maintenance, and were confirmed in the expert stage in terms of relevance to the research objective. Table 1 presents the indicators and their improvement direction.

Table 1. World-class outcome indicators, quantitative improvement direction, and literature support

Code	Outcome indicator	Improvement direction and literature support
B1	Reduction of Mean Time to Repair	Predictive maintenance and AI-based automotive maintenance literature emphasizes meaningful reductions in MTTR, downtime, and recovery time (Mahale et al., 2025).
B2	Increase in service availability ratio	Digital twin, predictive maintenance, and system-health management literature emphasizes increased availability and service stability (Khan et al., 2025).
B3	Reduction of failure rate	Predictive maintenance, condition monitoring, and AI-based maintenance literature emphasizes fewer sudden failures and higher reliability (Li et al., 2024).
B4	Reduction of maintenance costs	Data-driven TPM frameworks explain cost reduction through reduced downtime, improved OEE, and better maintenance-event control (Lucantoni et al., 2025).
B5	Increase in Overall Equipment Effectiveness	TPM and world-class manufacturing consider OEE as a core indicator linking maintenance, quality, and production performance (Mouhib et al., 2025).
B6	Reduction of production scrap	AI-based automotive quality literature reports defect reduction and movement toward zero-defect quality as outcomes of AI in quality control (Morales Matamoros et al., 2025).

After extracting the initial capabilities and outcome indicators, content validity was evaluated using CVR and I-CVI in response to the second research question. The purpose of this stage was to ensure that the capabilities and indicators were both necessary and relevant to the research topic from the experts' perspective.

Table 2. Content validity results for capabilities and indicators

Validation index	Acceptance criterion	Total number of items	Confirmed items	Confirmation percentage	Result
CVR	≥ 0.62	26	26	100%	Necessity of all items confirmed
I-CVI	≥ 0.80	26	26	100%	Relevance of all items confirmed
S-CVI/Ave	≥ 0.90	—	—	—	0.91; highly desirable

The content validity results showed that the capabilities and indicators extracted from thematic analysis had sufficient content adequacy from the experts' perspective. Therefore, no capability was removed solely due to weak content validity, and the initial capabilities entered the fuzzy Delphi stage for more precise screening.

After content validation, a single-round fuzzy Delphi process was conducted to screen and select the core capabilities. The acceptance criterion for a capability was a crisp value equal to or greater than 8. Based on this criterion, 9 out of the 20 initial capabilities were stabilized as the core AI capabilities for World-Class TPM in response to the third research question.

Table 3. Core capabilities selected through fuzzy Delphi

Code	Core capability	AI tool/logic	Crisp value	Result
A1	Real-time communication network	GNN	8.905	Accepted
A2	Edge processing	Compressed DNN	9.366	Accepted
A3	Smart sensors	1D-CNN	9.662	Accepted
A4	Dynamic failure prediction	LSTM and attention mechanism	9.788	Accepted
A5	Preventive quality control	YOLOv8	9.013	Accepted
A6	Intelligent knowledge management	Transformer/NLP	8.256	Accepted
A7	Resilient supply chain	GNN and reinforcement learning	8.905	Accepted
A8	Intelligent continuous improvement	Autoencoder and XGBoost	8.830	Accepted
A9	Cyber–physical security	Anomaly-detection DNN	9.267	Accepted

After the single-round fuzzy Delphi process, these 9 capabilities were accepted as core capabilities because their crisp values were equal to or greater than the threshold of 8. In contrast, 11 capabilities did not reach the acceptance threshold and were excluded from causal analysis. These excluded capabilities included operational anomaly detection, failure simulation, real-

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time visual/video monitoring, dynamic adaptation, energy management, root-cause analysis, demand prediction, self-adjusting maintenance, synthetic data platform, physics-based equipment modeling, and self-healing systems.

The fuzzy Delphi results indicate that the selected capabilities are not merely isolated technological tools; rather, they form a complementary set of communication, data, analytical, quality, knowledge, supply, security, and learning capabilities. The highest crisp value belonged to dynamic failure prediction, indicating that experts considered the transition from reactive maintenance to predictive maintenance as one of the central axes of AI-based TPM transformation. Expert consensus was also examined to ensure that the selected capabilities were not accepted solely based on crisp values. The results showed that the 9 selected capabilities not only passed the crisp-value threshold, but were also defensible in terms of expert agreement.

After stabilizing the selected capabilities through fuzzy Delphi, the AI tools corresponding to each capability were conceptually validated against the literature. The purpose of this stage was to determine whether the AI technology or logic assigned to each capability was consistent with its data type, operational problem, and managerial function.

Table 4. Literature-based conceptual validation of AI tools for selected capabilities

Code	Selected capability	AI tool/logic	Conceptual validation logic	Supporting literature
A1	Real-time communication network	GNN	Graph neural networks are suitable for modeling relationships among equipment, stations, edge nodes, and data flows because industrial network structures can be represented as graphs.	Wang & Liang, 2025; Mouhib et al., 2025
A2	Edge processing	Compressed DNN	Edge processing and compact deep-learning models perform preprocessing and feature extraction close to the data source and are suitable for reducing latency, data-transfer volume, and supporting real-time analytics.	Wang et al., 2025
A3	Smart sensors	1D-CNN	One-dimensional convolutional networks are appropriate for extracting patterns from vibration, sound, temperature, pressure, and OBD data and can serve as the starting point for condition monitoring and failure prediction.	Mahale et al., 2025; Andrianandrianina Johanesa et al., 2024
A4	Dynamic failure prediction	LSTM and attention mechanism	LSTM and attention mechanisms are suitable for learning time-dependent patterns, predicting failures, estimating remaining useful life, and extracting equipment-health indicators.	Mahale et al., 2025; Taoufyq et al., 2025
A5	Preventive quality control	YOLOv8	YOLOv8 and deep vision models are suitable for detecting surface, welding, painting, and component defects in automotive lines and preventing defects from turning into scrap and rework.	Morales Matamoros et al., 2025; Liang & Chen, 2025
A6	Intelligent knowledge management	Transformer/NLP	Transformers and NLP are suitable for extracting and structuring knowledge from failure reports, repair records, manuals, and technicians' notes.	Giordano & Fantoni, 2025; Hershowitz et al., 2024
A7	Resilient supply chain	GNN and reinforcement learning	GNNs can model supplier, warehouse, production, and maintenance networks, while reinforcement learning supports adaptive decision-making in spare-parts planning and routing.	Wang & Liang, 2025; Kotecha & del Rio-Chanona, 2025
A8	Intelligent continuous improvement	Autoencoder and XGBoost	Autoencoders are suitable for anomaly detection and latent-pattern extraction, while XGBoost supports performance classification and prioritization of corrective actions.	Li et al., 2024; Lucantoni et al., 2025
A9	Cyber–physical security	Anomaly-detection DNN	Deep anomaly-detection models are suitable for identifying cyber–physical threats, abnormal data patterns, and suspicious behavior in industrial networks.	Yazdinejad et al., 2023; Wang et al., 2025

The conceptual validation results showed that the AI tools corresponding to the selected capabilities were consistent with the problem nature of each capability. Thus, the selected capabilities were defensible both from the perspective of expert consensus and from the perspective of conceptual support in the literature. This stage ensured that the capabilities entered fuzzy DEMATEL based on a refined, consensual, and conceptually supported set.

After stabilizing the 9 core capabilities, confirming the outcome indicators, and conceptually validating the AI tools, fuzzy DEMATEL was conducted to analyze causal relationships in response to the fourth research question. The output of this stage was the crisp total-relation matrix T. Based on matrix T, D, R, D+R, and D−R indices were calculated.

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Table 5. Fuzzy DEMATEL indices for capabilities and outcomes

Code	Capability/indicator	D	R	D+R	D−R	Importance	Causal role
A1	Real-time communication network	0.520	0.505	1.025	0.015	Important	Weak/borderline dependent
A2	Edge processing	0.583	0.475	1.058	0.108	Important	Weak cause
A3	Smart sensors	0.553	0.530	1.083	0.023	Important	Weak/borderline dependent
A4	Dynamic failure prediction	1.024	0.488	1.512	0.536	Very important	Strong cause
A5	Preventive quality control	0.879	0.533	1.412	0.346	Very important	Strong cause
A6	Intelligent knowledge management	0.676	0.420	1.096	0.256	Important	Weak cause
A7	Resilient supply chain	0.987	0.515	1.502	0.472	Very important	Strong cause
A8	Intelligent continuous improvement	0.936	0.526	1.462	0.410	Very important	Strong cause
A9	Cyber–physical security	0.487	0.462	0.949	0.025	Moderate	Weak/borderline dependent
B1	Reduction of Mean Time to Repair	0.000	0.355	0.355	−0.355	Low importance	Strong dependent
B2	Increase in service availability ratio	0.000	0.365	0.365	−0.365	Low importance	Strong dependent
B3	Reduction of failure rate	0.000	0.374	0.374	−0.374	Moderate	Strong dependent
B4	Reduction of maintenance costs	0.000	0.380	0.380	−0.380	Moderate	Strong dependent
B5	Increase in Overall Equipment Effectiveness	0.000	0.373	0.373	−0.373	Moderate	Strong dependent
B6	Reduction of production scrap	0.000	0.344	0.344	−0.344	Low importance	Strong dependent

For interpreting prominence, the quartiles of D+R were used. Values below 0.373 were classified as low importance; values from 0.373 to below 1.025 as moderate; values from 1.025 to below 1.412 as important; and values equal to or greater than 1.412 as very important. For interpreting causal role, the median of D−R was 0.025 and the MAD was 0.289; therefore, D−R values equal to or greater than 0.314 were classified as strong causes. Accordingly, A4, A5, A7, and A8 were classified as strong and very important causal capabilities.

The fuzzy DEMATEL results show that dynamic failure prediction, preventive quality control, resilient supply chain, and intelligent continuous improvement are not only important capabilities, but also have greater power to activate other capabilities and world-class outcomes in the influence network. In contrast, B1 to B6 mainly play outcome roles and are more dependent than influential. The D values for the B indicators were set to zero because, in the initial relationship matrix, performance indicators were modeled as final outcomes and their corresponding rows were therefore considered zero.

To ensure the reliability of DEMATEL results, stability analysis was conducted under 5%, 10%, and 15% perturbation levels. At each perturbation level, 100 independent iterations were performed, and the mean outputs were compared with the baseline state.

Table 6. Summary of DEMATEL stability validation

Scenario	Perturbation level	Mean change in prominence of A capabilities	Mean change in dependence of B outcomes	Spearman coefficient	Ranking status	Causal-role status
S1	5%	0.160%	0.274%	1.000	Stable	Stable
S2	10%	0.358%	0.548%	1.000	Stable	Stable
S3	15%	0.605%	0.822%	1.000	Stable	Stable

The stability results showed that the causal role of the main capabilities, especially A4, A5, A7, and A8, was preserved under controlled perturbations. The mean change in the prominence of A capabilities remained below 1% even at the 15% perturbation level. Spearman's coefficient remained 1.000 in all three scenarios, indicating complete ranking stability. In terms of causal role, the sign of D−R also remained stable for the main capabilities, and B1 to B6 preserved their outcome role.

After validating the stability of DEMATEL results, a threshold was determined to draw the causal diagram and display meaningful relationships. The purpose of thresholding was to eliminate weak relationships and prevent excessive complexity in the influence diagram. Four thresholding criteria were examined: median, mean, mean minus standard deviation, and mean plus standard deviation.

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Table 7. Comparison of DEMATEL thresholding criteria

Threshold criterion	Value	Remaining relationships	Status	Sensitivity to outliers	Justification	Supporting reference
Mean + standard deviation	0.082	32	Very sparse	Highly sensitive	Weak	Li et al., 2025
Mean	0.054	58	Relatively logical	Sensitive	Good	Nyimbili et al., 2023
Median	0.044	72	Logical	Robust	Excellent	Ebrahimi, 2023
Mean − standard deviation	0.026	104	Very dense	Highly sensitive	Weak	Ebrahimi, 2023

The comparison showed that the mean plus standard deviation made the network excessively sparse and could remove important relationships. The mean minus standard deviation made the network overly dense and retained many weak relationships. The mean produced a relatively logical structure, but it was more sensitive to large values. The median produced a better balance because it was more robust to outliers while preserving the main relationships and reducing excessive network density. Therefore, 0.044 was selected as the final threshold.

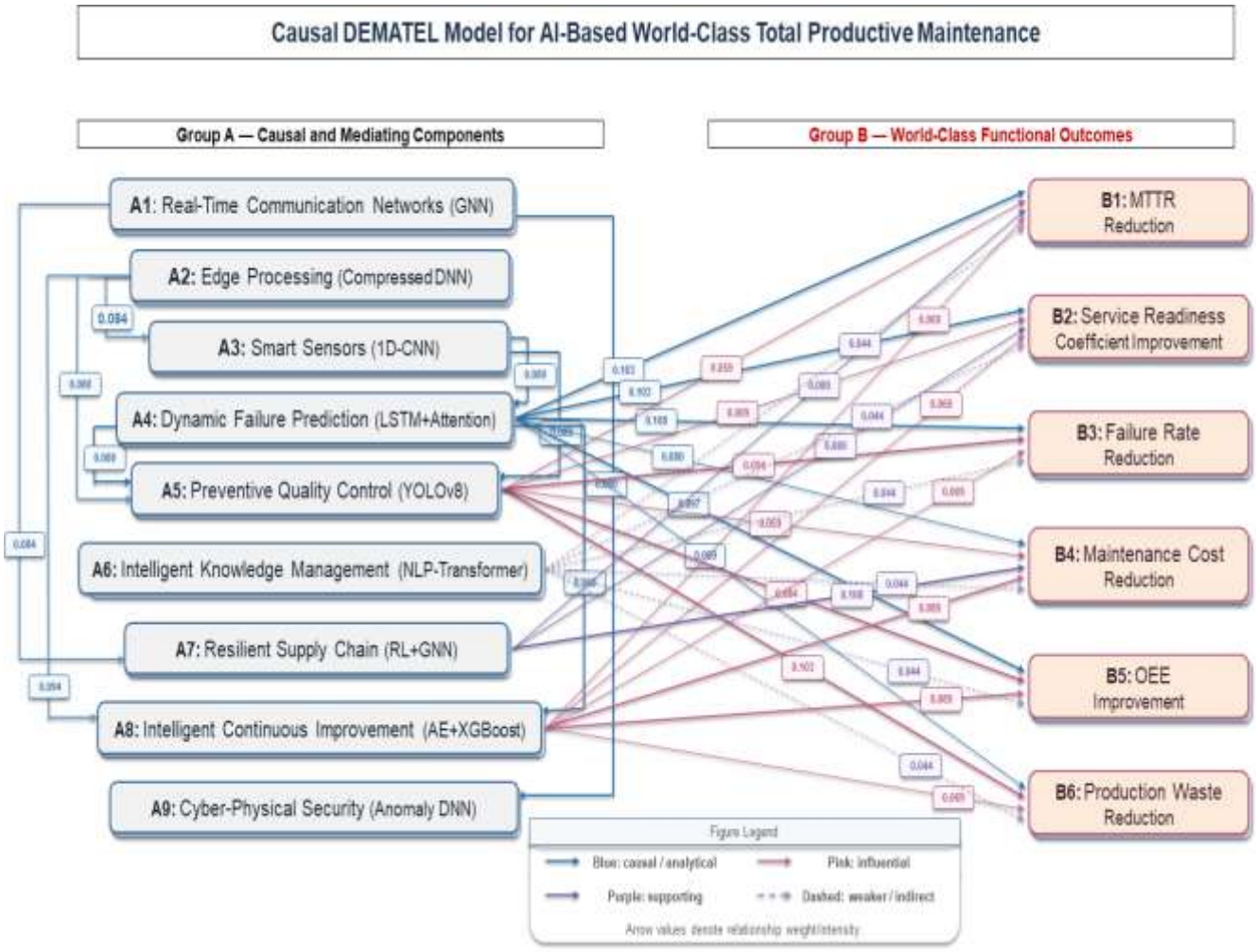


Figure 1. Fuzzy DEMATEL causal diagram for AI capabilities and world-class outcome indicators

In this diagram, the nodes include the 9 capabilities A1 to A9 and the 6 outcome indicators B1 to B6. Edges represent only those relationships whose values in matrix T are equal to or greater than the threshold of 0.044. The weight of each edge is the corresponding tij value rounded to three decimals. The direction of each edge is drawn from the influencing capability to the influenced capability or indicator. To interpret the causal position of the nodes, the horizontal axis represents D+R prominence and the vertical axis represents D−R causality. Capabilities with positive D−R values are located in the cause region, whereas capabilities or indicators with negative D−R values are located in the effect region.

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4. Discussion and Conclusion

The present study sought to identify, validate, and causally analyze the artificial intelligence capabilities required to advance Total Productive Maintenance (TPM) toward World-Class standards in the automotive industry. The findings showed that, of the 20 initially identified capabilities, nine were stabilized through the fuzzy Delphi process as core capabilities: real-time communication network, edge processing, smart sensors, dynamic failure prediction, preventive quality control, intelligent knowledge management, resilient supply chain, intelligent continuous improvement, and cyber–physical security. The results are important because they indicate that AI-based transformation of TPM cannot be reduced to the implementation of a single predictive algorithm or isolated maintenance technology. Rather, World-Class TPM requires an interconnected configuration of infrastructural, analytical, quality-related, knowledge-related, supply-chain, learning, and security capabilities. This interpretation is consistent with the growing convergence between TPM and Industry 4.0, according to which conventional TPM principles increasingly need to be integrated with connectivity, data analytics, intelligent decision-making, and automation (Mouhib et al., 2025). It also supports data-driven approaches to TPM that view maintenance performance as the outcome of an integrated analytical system rather than a collection of separate technical interventions (Lucantoni et al., 2025).

Among the nine accepted capabilities, dynamic failure prediction obtained the highest fuzzy Delphi score and subsequently emerged as the strongest causal capability in the DEMATEL analysis. Its D−R value of 0.536 and high prominence confirmed that it not only occupied a central position in the system but also exerted substantial influence on other capabilities and world-class outcomes. This result shows that the transition from reactive or calendar-based maintenance toward prediction-oriented maintenance represents a central pathway for transforming automotive TPM. Dynamic failure prediction enables organizations to recognize degradation patterns before functional failure, estimate equipment health, schedule interventions more precisely, and reduce emergency maintenance. This finding is consistent with research showing that deep learning architectures can learn nonlinear and temporal degradation patterns and support fault prediction, anomaly recognition, and remaining useful life estimation (Li et al., 2024). It also agrees with systematic evidence indicating that predictive maintenance increasingly depends on machine learning models capable of combining historical failure information with continuously generated condition data (Taoufyq et al., 2025). Studies focused specifically on automotive applications similarly emphasize the capacity of AI-driven diagnosis to detect vehicle and equipment faults earlier and improve maintenance decisions (Hossain et al., 2024). The present finding therefore confirms that predictive intelligence should be treated as a leverage capability in World-Class TPM rather than merely as another maintenance application.

The importance assigned to smart sensors and edge processing further explains why dynamic prediction cannot operate independently. Smart sensors generate the vibration, temperature, pressure, sound, and other condition-monitoring signals on which predictive algorithms depend, while edge processing enables relevant computations to be performed close to the data source. Although these capabilities were not among the strongest causes in the DEMATEL network, their accepted Delphi scores demonstrate their infrastructural necessity. This distinction is significant: an enabling capability may not exert the greatest causal influence but may still be indispensable to the functioning of higher-level analytical capabilities. Evidence from Industry 4.0 confirms that AI-supported predictive maintenance requires continuous acquisition of reliable condition data from industrial assets (Andrianandrianina Johanesa et al., 2024). Similarly, AI-driven vehicle predictive-maintenance research highlights the importance of sensing architecture, real-time monitoring, and suitable data pipelines in converting analytical models into operational maintenance systems (Mahale et al., 2025). The growing demand for low-latency anomaly detection also supports the role of edge-oriented data infrastructure because rapid industrial decisions may lose operational value if large volumes of sensor data must first be transferred to distant computing environments (Wang & Liang, 2025).

Preventive quality control emerged as another strong and highly prominent causal capability. This finding extends the traditional boundaries of TPM by demonstrating that maintenance and quality should not be treated as isolated functional areas. Equipment deterioration often becomes visible through deviations in product quality before complete machine failure occurs. Welding defects, dimensional irregularities, surface defects, assembly errors, or changes in process consistency can therefore serve as indirect indicators of equipment health. The strong causal position of preventive quality control indicates that AI-based inspection can contribute not only to detecting defective products but also to identifying process deterioration and initiating maintenance action before larger losses emerge. This finding aligns with the systemic review by Morales Matamoros et al.,

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which demonstrates the expanding role of AI in detecting automotive quality defects and improving quality-control processes (Morales Matamoros et al., 2025). It is also supported by research on trustworthy YOLO-based industrial defect detection, showing that deep computer vision architectures can identify defects rapidly and reliably in manufacturing environments (Liang & Chen, 2025). Therefore, the present results strengthen the conceptual connection between TPM, predictive maintenance, and zero-defect manufacturing.

Resilient supply chain was also identified as one of the strongest causal capabilities. This finding is particularly meaningful because maintenance studies often concentrate primarily on equipment condition while treating spare-parts logistics and supply availability as secondary issues. In practice, however, accurately predicting a failure does not necessarily reduce downtime if required parts, tools, or resources are unavailable when maintenance intervention becomes necessary. The causal importance of resilient supply chain therefore suggests that world-class maintenance performance depends on integrating maintenance intelligence with supplier networks, spare-parts inventories, warehouse operations, and production scheduling. Graph neural networks and multi-agent reinforcement learning have demonstrated the ability to represent complex supply-chain relationships and support adaptive inventory-control decisions (Kotecha & del Rio-Chanona, 2025). Similarly, graph-based reinforcement learning and self-attention mechanisms have been applied to dynamic route optimization in supply chains, indicating the potential of AI to improve responsive logistics decisions under changing conditions (Wang et al., 2025). In TPM terms, these technologies can help ensure that maintenance predictions are converted into timely operational responses rather than remaining analytical outputs without implementation capacity.

The identification of intelligent continuous improvement as a strong causal capability represents another important result. TPM has traditionally been built around the elimination of losses, standardized improvement activities, and sustained enhancement of equipment effectiveness. The present results indicate that AI can strengthen this philosophy by continuously identifying recurring failure patterns, classifying performance deviations, evaluating corrective actions, and learning from previous interventions. Therefore, AI-enabled TPM should not stop at predicting the next failure; it should convert accumulated operational data into organizational learning and improvement cycles. This interpretation aligns with data-driven TPM frameworks emphasizing the use of analytics to support maintenance prioritization and continuous performance enhancement (Lucantoni et al., 2025). It is also consistent with established world-class manufacturing principles in which maintenance must contribute to productivity, quality, responsiveness, and competitive performance (Farsijani & Dehghan, 2016). Earlier research connecting TPM with group technology and world-class manufacturing similarly suggests that maintenance creates strategic value when it is embedded within broader production-improvement systems rather than confined to equipment repair (Farsijani et al., 2012).

Intelligent knowledge management was identified as an important causal capability, although its causal intensity was lower than that of the four strongest leverage capabilities. This finding demonstrates that accumulated maintenance knowledge represents a strategic resource for AI-based TPM. Automotive organizations produce substantial quantities of unstructured information through work orders, maintenance logs, failure reports, manuals, inspection notes, and technicians' experiences. Without intelligent mechanisms for structuring and retrieving this information, valuable knowledge may remain fragmented or disappear when experienced employees leave the organization. Natural language processing provides an opportunity to transform these textual repositories into reusable maintenance knowledge. Research has demonstrated that causal knowledge can be extracted from lengthy maintenance documents, providing structured relationships that can support diagnosis and decision-making (Hershowitz et al., 2024). Likewise, NLP-based decomposition of maintenance actions into subtasks in an automotive company illustrates the capacity of AI to formalize maintenance knowledge and make operational experience more accessible and reusable (Giordano & Fantoni, 2025). The present findings therefore suggest that intelligent knowledge management acts as a bridge between human expertise and data-driven maintenance.

Real-time communication networks and cyber–physical security showed weaker or borderline causal roles than the major leverage capabilities. These results should not be interpreted as evidence that these dimensions are less necessary. Rather, they appear to function mainly as enabling infrastructures that make other AI capabilities feasible. Real-time communication networks allow equipment, sensors, edge nodes, analytical platforms, and decision systems to exchange information rapidly. Graph-oriented architectures are particularly relevant because manufacturing environments consist of connected machines,

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production cells, logistics nodes, and data-processing components that can naturally be modeled as network structures. Research applying graph neural networks to complex operational networks supports their suitability for representing relational dependencies and enabling adaptive decision processes (Wang et al., 2025). Similarly, the increasing integration of TPM with Industry 4.0 requires interconnected digital infrastructure capable of integrating data across production and maintenance functions (Mouhib et al., 2025). Thus, the weaker causal classification of communication infrastructure should be understood as reflecting its enabling rather than outcome-driving position.

Cyber–physical security presents a similar case. Greater connectivity creates new vulnerabilities because manipulated sensor data, unauthorized network access, or abnormal cyber behavior can undermine the accuracy of maintenance predictions and potentially create unsafe production decisions. The acceptance of cyber–physical security as a core capability therefore confirms that trustworthy intelligent maintenance requires protection of both physical assets and the data environments used to monitor them. Ensemble deep learning models developed for cyber-threat hunting in industrial Internet of Things systems demonstrate the relevance of AI-based anomaly recognition for protecting industrial networks (Yazdinejad et al., 2023). The increasing use of real-time intelligent data infrastructures similarly reinforces the need to ensure the integrity and security of the information on which industrial decisions are based (Wang & Liang, 2025). Consequently, cyber–physical security can be interpreted as a foundational safeguard whose absence may weaken the entire AI-enabled TPM system even if its direct causal influence on performance outcomes is comparatively limited.

The results concerning the six World-Class TPM indicators are also noteworthy. Reduction in Mean Time to Repair, increase in service availability, reduction in failure rate, reduction in maintenance costs, increase in Overall Equipment Effectiveness, and reduction in production scrap all appeared primarily as dependent outcomes. This means that these indicators should be regarded as consequences of capability development rather than independent drivers of transformation. This finding corresponds with the traditional logic of TPM, in which indicators such as OEE, equipment availability, failure rates, and repair times are used to assess whether maintenance practices are generating operational improvement (Toke & Kalpande, 2023). Predictive maintenance literature similarly associates intelligent maintenance with reduced failures, improved availability, faster maintenance response, and lower maintenance-related losses (Hector & Panjanathan, 2024). AI-driven vehicle maintenance studies further suggest that earlier and more precise fault diagnosis can contribute to reduced unexpected failures and improved equipment availability (Mahale et al., 2025). Therefore, the DEMATEL structure provides an important managerial distinction between what organizations should develop—AI capabilities—and what they should ultimately expect to improve—maintenance and production performance indicators.

The relationship between the selected capabilities and OEE is particularly important because OEE captures the combined effects of availability, performance, and quality. The findings imply that OEE improvement is unlikely to emerge from an isolated AI intervention. Dynamic failure prediction supports availability, preventive quality control supports the quality component, resilient supply chains reduce maintenance delays, and intelligent continuous improvement strengthens sustained performance. This systemic interpretation is consistent with attempts to integrate TPM and Industry 4.0 into standardized frameworks in which digital technologies reinforce interconnected TPM objectives rather than isolated maintenance tasks (Mouhib et al., 2025). It also corresponds with data-driven TPM approaches emphasizing the need to connect maintenance analytics with organizational performance indicators (Lucantoni et al., 2025). Accordingly, World-Class TPM should be viewed as an integrated performance system generated by multiple mutually reinforcing AI capabilities.

The results also have implications for digital transformation in the Iranian automotive context. Research at Iran Khodro has shown that digital transformation based on Fourth Industrial Revolution technologies requires coordinated development of technological, structural, and managerial dimensions (Mozaffari Mehr & Taghavi Fard, 2024). Similarly, implementation of Industry 4.0 for sustainable development in Iran Khodro has been found to depend on broader organizational and infrastructural readiness rather than simple acquisition of advanced technologies (Ardehi et al., 2023). The present results reinforce these observations by showing that AI-enabled TPM must be developed as a network of complementary capabilities. An organization that invests in sophisticated predictive algorithms without adequate sensing, communication, knowledge, supply-chain, and security infrastructure may therefore obtain limited benefits. The results favor a portfolio-based approach to AI transformation in which technology adoption is coordinated with operational and organizational capability development.

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Another methodological contribution concerns the use of fuzzy DEMATEL to distinguish leverage capabilities from dependent outcomes and enabling infrastructures. The application of DEMATEL is consistent with its use in complex multi-criteria systems where factors influence one another rather than existing independently (Govindan et al., 2015). DEMATEL-based studies in other complex decision environments similarly demonstrate the value of separating driving factors from dependent ones and identifying central elements in interconnected systems (Nyimbili et al., 2023). More recent integrated DEMATEL applications further show how causal modeling can reveal hierarchical and interdependent structures that simple importance ranking may obscure (Li et al., 2025). In the present study, this distinction was crucial because a capability could be highly necessary without being a dominant causal driver. The resulting structure therefore provides a more informative basis for investment prioritization than a conventional ranking alone.

The robustness analysis further strengthens confidence in these conclusions. Under perturbation levels of 5%, 10%, and 15%, the ranking of capabilities remained stable, with Spearman coefficients of 1.000, while the causal roles of the main capabilities and the dependent status of the outcome indicators were preserved. This stability indicates that the identification of dynamic failure prediction, preventive quality control, resilient supply chain, and intelligent continuous improvement as leverage capabilities was not highly sensitive to modest changes in the relationship matrix. Furthermore, the use of a threshold of 0.044 for displaying meaningful DEMATEL relationships provided a balance between excessive network density and excessive simplification. The importance of analytically justified threshold determination has been emphasized in DEMATEL methodological research because different threshold criteria can substantially alter the interpretability of causal networks (Ebrahimi, 2023). Thus, the combination of fuzzy evaluation, causal analysis, threshold assessment, and stability testing enhances the methodological defensibility of the proposed capability network.

Overall, the results suggest that the transformation of TPM toward World-Class standards should be understood as a system-level transition from reactive maintenance toward an interconnected intelligent maintenance ecosystem. Dynamic failure prediction provides anticipatory intelligence; preventive quality control links equipment conditions to product conformity; resilient supply chains ensure that maintenance decisions can be operationally executed; and intelligent continuous improvement converts accumulated data into learning and corrective action. At the same time, smart sensors, edge processing, communication networks, knowledge management, and cyber–physical security provide the infrastructure through which these leverage capabilities can function reliably. Digital-twin research further supports such an integrated view by demonstrating how physical assets, operational data, predictive analytics, and maintenance decisions can be connected within a continuously updated digital environment (Khan et al., 2025). The study therefore contributes to the literature by moving the concept of AI-based TPM beyond isolated algorithms and toward a causally structured portfolio of complementary capabilities capable of supporting World-Class automotive manufacturing.

This study has several limitations that should be considered when interpreting its findings. First, the empirical judgments were obtained from a relatively small purposive panel of experts from Iran Khodro and SAIPA; although these experts represented maintenance, production, quality, information technology, artificial intelligence, and supply-chain functions, the findings may reflect characteristics of large Iranian automotive manufacturers and may not be fully transferable to smaller automotive firms or manufacturers operating in different institutional and technological environments. Second, fuzzy Delphi and fuzzy DEMATEL rely on expert judgment, and therefore the estimated relationships represent informed perceptions rather than causal effects observed through longitudinal operational data. Third, the study identified and prioritized capabilities at a strategic level but did not empirically implement the proposed AI tools within production lines or measure their actual effects on MTTR, availability, failure rate, maintenance cost, OEE, and scrap. Fourth, although perturbation analysis supported the stability of the causal structure, alternative modeling assumptions or different expert groups could yield somewhat different influence intensities. Finally, technological capabilities in artificial intelligence evolve rapidly, meaning that new tools and architectures may emerge that alter the relative importance or operational feasibility of some identified capabilities.

Future studies should validate the proposed capability structure using larger and more diverse samples of automotive manufacturers and should compare results across countries, firm sizes, production technologies, and levels of digital maturity. Longitudinal and intervention-based studies could implement selected capabilities in real production environments and quantify their effects on equipment availability, failure rates, repair time, maintenance costs, OEE, quality defects, and production scrap. Researchers may also develop a structural implementation architecture showing the sequential dependencies among the nine

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capabilities and identifying maturity levels for progressive adoption. Combining DEMATEL with methods such as ISM, ANP, Bayesian networks, system dynamics, or structural equation modeling could provide additional insight into hierarchy, feedback relationships, uncertainty, and empirical causal pathways. Future studies could additionally investigate human factors, employee acceptance, AI explainability, workforce competencies, governance, investment costs, return on investment, ethical issues, and cybersecurity risks associated with intelligent TPM. Comparative investigations between conventional TPM, Industry 4.0-enabled TPM, and emerging Industry 5.0 maintenance systems would also help determine how human-centeredness, resilience, and intelligent automation modify capability priorities.

Automotive managers should avoid approaching AI-enabled maintenance as a collection of independent technology projects and instead establish a coordinated capability-development roadmap. Priority investment should be directed toward the four leverage capabilities identified in this study—dynamic failure prediction, preventive quality control, resilient supply chain, and intelligent continuous improvement—while simultaneously ensuring that the required infrastructures of smart sensing, edge processing, real-time communication, intelligent knowledge management, and cyber–physical security are sufficiently mature. Managers should connect predictive alerts directly to maintenance work orders, spare-parts planning, quality-control systems, and production scheduling so that analytical outputs generate executable actions. Maintenance and quality databases should be integrated, historical repair knowledge should be systematically captured, and cross-functional teams involving maintenance, production, IT, quality, data specialists, and supply-chain personnel should jointly govern the transformation. Performance dashboards should continuously track MTTR, availability, failure rates, maintenance costs, OEE, and scrap so that the contribution of each AI capability can be evaluated over time. A phased implementation beginning with high-criticality equipment and expanding after measurable operational gains would reduce implementation risk and help organizations progress systematically toward World-Class TPM.

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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