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THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) ON MECHANICAL ENGINEERING TECHNOLOGY IN VIETNAM

Hoang Anh Thu

Faculty of Electrical and Electronic Engineering Technology, Dai Nam University, Hanoi, Vietnam

ABSTRACT

The rapid advancement of Artificial Intelligence is fundamentally transforming virtually every sector of modern industry and engineering worldwide. From the perspective of advanced mechanical engineering research and manufacturing methodologies, this study systematically investigates the impact of AI on Vietnam's Mechanical Engineering Technology sector during the period from 2020 to 2026. Recent industrial data reveal a remarkable increase in AI adoption among Vietnamese mechanical manufacturing enterprises, rising from approximately 10÷15% in 2020 to nearly 35÷40% during 2024÷2026. This technological transformation has created significant opportunities for optimizing structural design, reducing manufacturing costs, improving production efficiency, and minimizing equipment downtime through predictive maintenance strategies.

Keyword: Artificial Intelligence; Mechanical Engineering Technology; Smart Manufacturing; Generative Design; Predictive Maintenance; Vietnam.

1. INTRODUCTION

The Fourth Industrial Revolution (Industry 4.0), driven primarily by Artificial Intelligence (AI), is fundamentally reshaping the technological foundations and manufacturing paradigms of modern industry worldwide [1-6]. AI is no longer confined to theoretical algorithms developed within computer science laboratories; instead, it has become deeply integrated into heavy industry, advanced manufacturing, mechatronics, and intelligent production systems [2, 7]. The unprecedented growth in parallel computing capability, the widespread deployment of the Industrial Internet of Things (IIoT), the emergence of massive industrial datasets, and continuous breakthroughs in deep learning architectures have collectively established AI as one of the most transformative technologies of the twenty-first century [8].

For the discipline of Mechanical Engineering Technology, which constitutes the foundation of virtually every industrial sector, AI represents a fundamental paradigm shift rather than merely another engineering tool. Modern mechanical engineers are no longer restricted to conventional analytical formulations or traditional numerical simulations that rely heavily on idealized assumptions. Instead, machine learning algorithms enable engineers to extract meaningful knowledge directly from complex, multivariate manufacturing data generated under real operating conditions [1, 4, 5]. Consequently, AI can identify hidden dynamic behaviors and nonlinear relationships that are difficult-or even impossible-to capture using conventional physics-based mathematical models alone.

In Vietnam, the mechanical engineering industry plays a strategic role in strengthening national industrial capability and technological self-reliance [7]. Nevertheless, for several decades, domestic manufacturing enterprises have faced persistent structural challenges, including relatively low labor productivity compared with neighboring countries, limited value-added localization, and heavy dependence on imported CNC technologies, engineering software, and advanced manufacturing equipment [8-10]. To address these challenges and accelerate industrial modernization, the Vietnamese Government issued Decision No. 749/QĐ-TTg, approving the National Digital Transformation Program toward 2025 with a Vision to 2030, in which manufacturing has been identified as one of the country's highest-priority sectors [3, 5, 6, 9, 10]. Within this strategic framework, integrating AI technologies into the mechanical manufacturing value chain should not be regarded merely as the adoption of new software tools; rather, it constitutes a national strategy for transforming labor-intensive manufacturing into intelligent, autonomous production systems capable of competing in the global market.

Against this background, this study pursues three primary research objectives. First, it systematically reviews the mathematical foundations and computational methodologies of AI technologies applied to advanced mechanical engineering. Second, it quantitatively evaluates the current state of AI implementation and its industrial impacts within Vietnam's manufacturing sector. Finally, it proposes an interdisciplinary strategic framework that aligns higher engineering education, industrial digital transformation, and national innovation policies to facilitate the sustainable integration of AI into Vietnam's future manufacturing ecosystem.

2. THEORETICAL BACKGROUND

2.1 Mathematical and technological foundations of artificial intelligence in advanced mechanical engineering

From a systems engineering perspective, Artificial Intelligence (AI) should not be regarded as an independent technology but rather as an integrated computational framework composed of multiple interrelated mathematical and engineering disciplines. Within modern mechanical engineering, AI architecture is primarily built upon three core technological pillars: Machine Learning and Deep Learning, Computer Vision, and Generative Artificial Intelligence [5]. Together, these technologies provide the computational intelligence required for autonomous decision-making, predictive modeling, adaptive control, and intelligent manufacturing.

The first pillar comprises Machine Learning (ML) and Deep Learning (DL), which constitute the computational core of intelligent mechanical systems [4]. Unlike conventional physics-based approaches that rely exclusively on analytical differential equations derived from conservation laws and continuum mechanics, machine learning constructs predictive mathematical models directly from experimental or industrial datasets. Consequently, ML algorithms can effectively capture nonlinear behaviors, stochastic uncertainties, and complex interactions that are often neglected in traditional deterministic models.

Among supervised learning techniques, predictive models are trained using labeled input-output datasets to establish mapping functions capable of forecasting engineering responses. In manufacturing applications, supervised learning has demonstrated remarkable performance in weld quality assessment, casting defect classification, tool wear prediction, dimensional accuracy evaluation, and surface roughness estimation. Algorithms such as Support Vector Machines (SVM), Random Forests, Gradient Boosting, and Artificial Neural Networks have become widely adopted owing to their superior predictive capabilities. In contrast, unsupervised learning focuses on discovering hidden structures embedded within unlabeled datasets. Clustering algorithms-including K-Means, Hierarchical Clustering, and DBSCAN-together with dimensionality reduction techniques such as Principal Component Analysis (PCA), are extensively employed for anomaly detection and health monitoring of rotating machinery. By analyzing vibration signatures, acoustic emissions, and spindle current signals, these methods can identify abnormal operating conditions without requiring prior fault labeling.

Another important branch of machine learning is Reinforcement Learning (RL), which enables intelligent systems to optimize their behavior through continuous interactions with dynamic environments. Based on Bellman's optimality principle, reinforcement learning algorithms maximize long-term cumulative rewards while adapting to changing operational conditions. In advanced manufacturing, RL has attracted considerable attention for adaptive robotic manipulation, autonomous machining parameter optimization, collision-free trajectory planning, and intelligent production scheduling within flexible manufacturing systems [1].

Recent advances in Deep Learning have further expanded the capabilities of AI in mechanical engineering. Deep Neural Networks (DNNs), consisting of multiple hidden layers, can automatically extract hierarchical features from large-scale industrial datasets without manual feature engineering [1]. Convolutional Neural Networks (CNNs) have become the dominant architecture for image-based defect inspection, surface quality evaluation, and dimensional measurement, whereas Recurrent Neural Networks (RNNs), Long Short-Term Memory

(LSTM), and Transformer-based architectures are particularly effective in processing sequential manufacturing data, including sensor signals, thermal histories, and equipment operating conditions.

The second technological pillar is Computer Vision (CV), which provides intelligent manufacturing systems with the capability to perceive and interpret physical environments. By integrating advanced image acquisition hardware with sophisticated image-processing algorithms, computer vision converts raw pixel information into meaningful engineering knowledge that supports automated inspection, dimensional metrology, object recognition, and robotic guidance. Modern computer vision systems typically perform a sequence of computational tasks, including image preprocessing, feature extraction, image segmentation, object detection, instance recognition, and three-dimensional reconstruction. High-resolution industrial cameras combined with deep learning architectures such as YOLO, Faster R-CNN, Mask R-CNN, and Vision Transformers enable manufacturing systems to detect microscopic defects, evaluate geometric tolerances, measure surface roughness, and identify workpiece positioning with exceptional precision and speed [2].

The integration of Computer Vision with industrial robotics has significantly enhanced manufacturing automation. Vision-guided robotic systems can autonomously recognize parts with arbitrary orientations, perform precision assembly, monitor machining processes in real time, and execute adaptive corrective actions without human intervention. Such capabilities substantially improve manufacturing flexibility while simultaneously reducing inspection costs and production errors. The third foundational component is Generative Artificial Intelligence (Generative AI) and Natural Language Processing (NLP). Although NLP was originally developed for human language understanding, recent breakthroughs in Transformer-based neural networks have dramatically expanded its applications into engineering design, digital manufacturing, and intelligent engineering assistants.

Particularly significant is the emergence of Generative Design, an AI-driven design paradigm that fundamentally transforms conventional engineering design methodology. Instead of manually developing a limited number of design alternatives based primarily on engineering experience, generative design algorithms automatically explore millions of feasible structural configurations within predefined design constraints [6]. This optimization process combines finite element analysis (FEA), topology optimization, evolutionary algorithms, and multi-objective optimization techniques to continuously evaluate candidate designs. The optimization simultaneously considers structural stiffness, mechanical strength, fatigue resistance, manufacturability, weight reduction, cost efficiency, and material utilization. As a result, engineers can identify globally optimal solutions that would be virtually impossible to obtain using conventional trial-and-error approaches.

Recent industrial applications have demonstrated that AI-assisted generative design can reduce component weight by 10÷40%, shorten product development cycles by 30÷60%, and substantially improve structural performance across aerospace, automotive, biomedical, and precision mechanical engineering industries [2, 7, 9]. Consequently, generative AI has become one of the most influential technological innovations driving the next generation of intelligent mechanical product development.

2.2 Integrated TAM–TOE Analytical Framework for AI Adoption in Manufacturing Industries

The successful implementation of Artificial Intelligence within manufacturing enterprises depends not only on technological maturity but also on a complex interaction among organizational, technological, and environmental factors. To comprehensively analyze AI adoption in Vietnam's mechanical engineering sector, this study adopts an integrated analytical framework combining the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework [3].

The Technology Acceptance Model (TAM) primarily focuses on individual users' behavioral intentions toward adopting new technologies. According to TAM, engineers' acceptance of AI systems is largely determined by two fundamental psychological constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Within mechanical manufacturing environments, engineers are unlikely to adopt AI-based diagnostic or predictive systems if software interfaces are excessively complex, require advanced programming expertise, or fail to provide tangible improvements in engineering efficiency. Conversely, AI solutions capable of reducing design iterations, shortening machining time, minimizing production defects, and improving engineering decision-making are considerably more likely to gain widespread acceptance.

While TAM explains technology adoption at the individual level, it does not adequately capture organizational and external influences. Therefore, this study further incorporates the Technology–Organization–Environment (TOE) framework to provide a comprehensive understanding of AI implementation at the enterprise level. The Technological Context evaluates factors such as compatibility, technological readiness, relative advantage, system integration capability, and digital infrastructure maturity [2, 3, 8]. Successful AI implementation requires seamless integration with existing Computer-Aided Design (CAD), Computer-Aided Manufacturing (CAM), Product Lifecycle Management (PLM), Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), and CNC control platforms [1].

The Organizational Context encompasses enterprise size, financial capacity, managerial commitment, innovation capability, digital culture, workforce competency, and data governance [3, 6, 8, 9]. Large manufacturing corporations generally possess sufficient financial resources to establish dedicated research laboratories and digital transformation centers [7]. In contrast, small and medium-sized enterprises (SMEs), which constitute the majority of Vietnam's manufacturing sector, frequently encounter severe limitations in capital investment, technical expertise, and digital infrastructure.

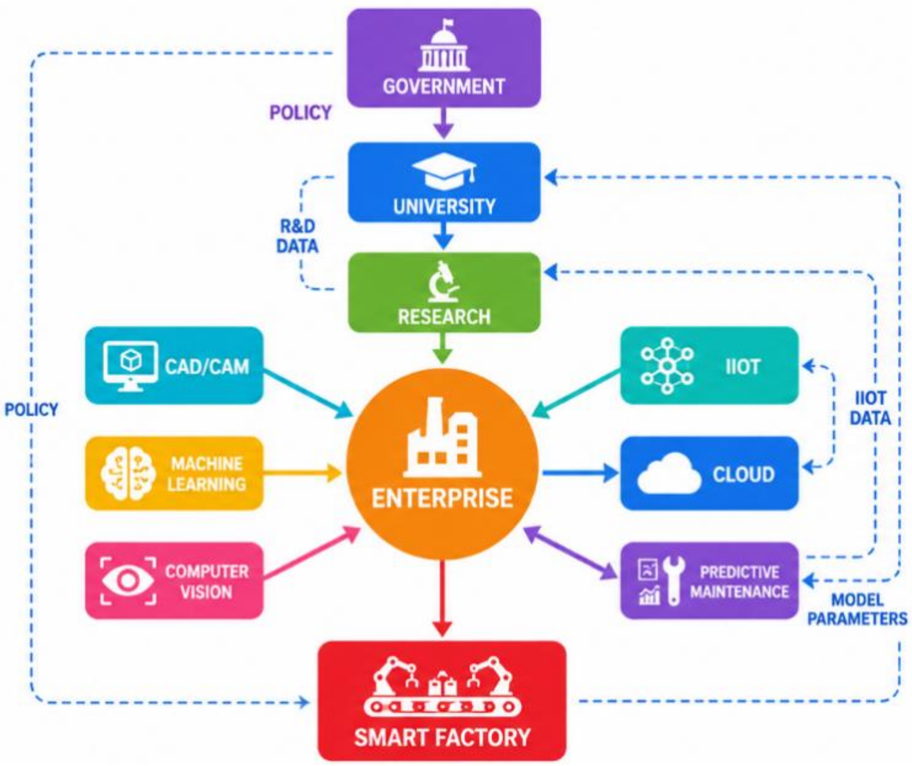

Fig. Integrated Smart Manufacturing Framework

Finally, the Environmental Context considers external pressures arising from government regulations, industrial standards, supply-chain requirements, market competition, and international collaboration [3, 4, 10]. Increasing demands from multinational corporations, foreign direct investment (FDI) enterprises, and global supply chains require Vietnamese manufacturers to comply with stringent quality standards, intelligent manufacturing practices, and digital traceability systems. Consequently, AI adoption has gradually evolved from a strategic competitive advantage into a fundamental requirement for maintaining long-term industrial competitiveness in the global manufacturing ecosystem [5].

3. APPLICATIONS AND QUANTITATIVE IMPACT ANALYSIS OF AI IN THE MECHANICAL ENGINEERING INDUSTRY IN VIETNAM

3.1. Analysis of Growth Dynamics and Trends in AI Adoption Across the Industry

Based on empirical studies and systematic survey data from 2020 to 2026, the overall picture of the digital maturity level of Vietnam's mechanical engineering industry has undergone significant quantitative shifts. The pace of technology adoption by enterprises in the industry is specifically illustrated in the growth dynamics chart below:

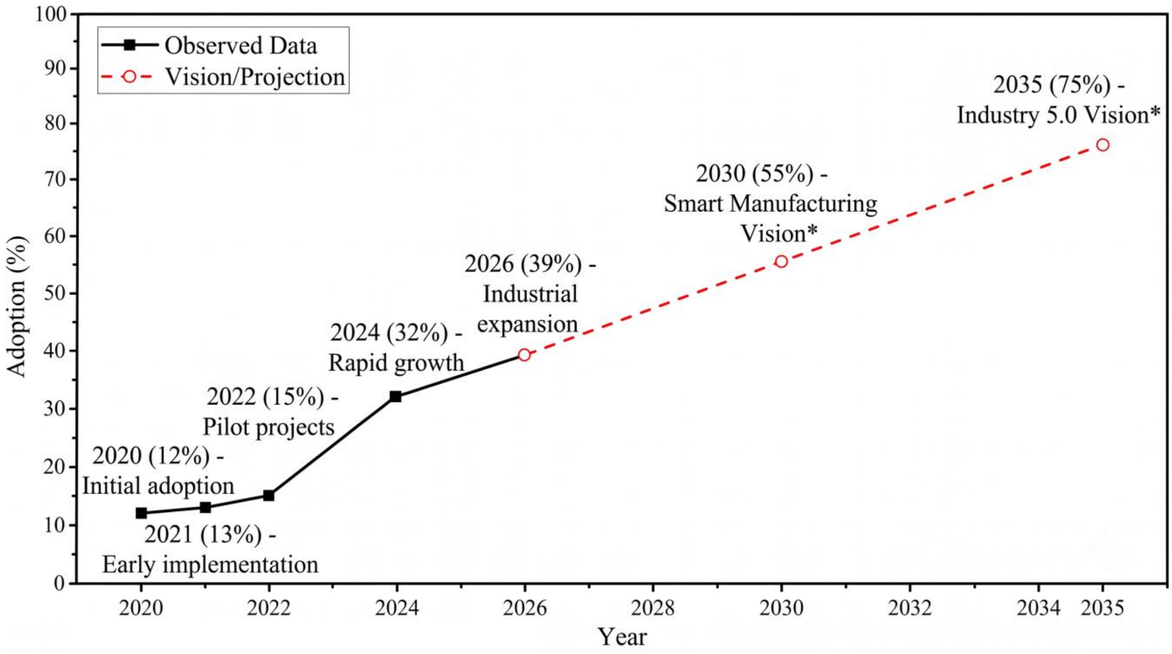

Figure 1: AI Adoption Trends in Vietnam's Mechanical Engineering Industry

The data reflects a nonlinear growth pattern [7]. The 2020÷2022 period saw slow growth due to limited awareness and disruptions in the global supply chain, with adoption rates fluctuating around the 12÷15% range [3, 9]. However, moving into the 2024÷2026 period, the market is expected to experience a strong surge, approaching the 35÷40% range [4, 6]. The core driver of this surge stems from intense competitive pressure and significant cost reductions in industrial IoT hardware, transforming AI from a luxury solution into a survival tool for businesses [5, 8, 10].

3.2. AI Applications in Generative Design and Nonlinear Structural Optimization

In the engineering design phase, traditional design methodologies-which rely on engineers experience-based thinking and manual trial-and-error processes-are being completely replaced by generative AI-based topological optimization workflows. When designing components subjected to complex dynamic loads-such as load-bearing beams in material handling equipment, transmission housings, or automotive body frames-AI algorithms directly run parallel finite element simulation loops. The system automatically analyzes millions of material distribution scenarios in three-dimensional space to find the optimal solution to a multi-objective problem: minimizing component mass while maximizing structural stiffness and bending and torsional moments.

Experimental results from several key research institutions and leading precision mold manufacturing companies in Vietnam demonstrate that this new design methodology delivers remarkably impressive results [6, 8]. Reducing excess material by 8% to 12% not only helps companies directly cut costs on purchasing expensive alloy steel billets or cast aluminum, but also significantly reduces the component's inertia, thereby saving operational energy and minimizing material fatigue under long-term operating conditions [10].

3.3. Applications of AI-Powered Computer Vision in Surface Quality Monitoring and Production Safety

In machining processes (CNC milling, turning) or pressure-based manufacturing, surface quality inspection is always a critical control challenge to ensure compliance with export standards. The intelligent defect inspection system, which utilizes deep computer vision, employs high-speed industrial cameras combined with optimized deep learning convolutional neural network algorithms such as ResNet or YOLO [5]. The real-time data processing flowchart for the system is structured as a linear feedback loop as shown below:

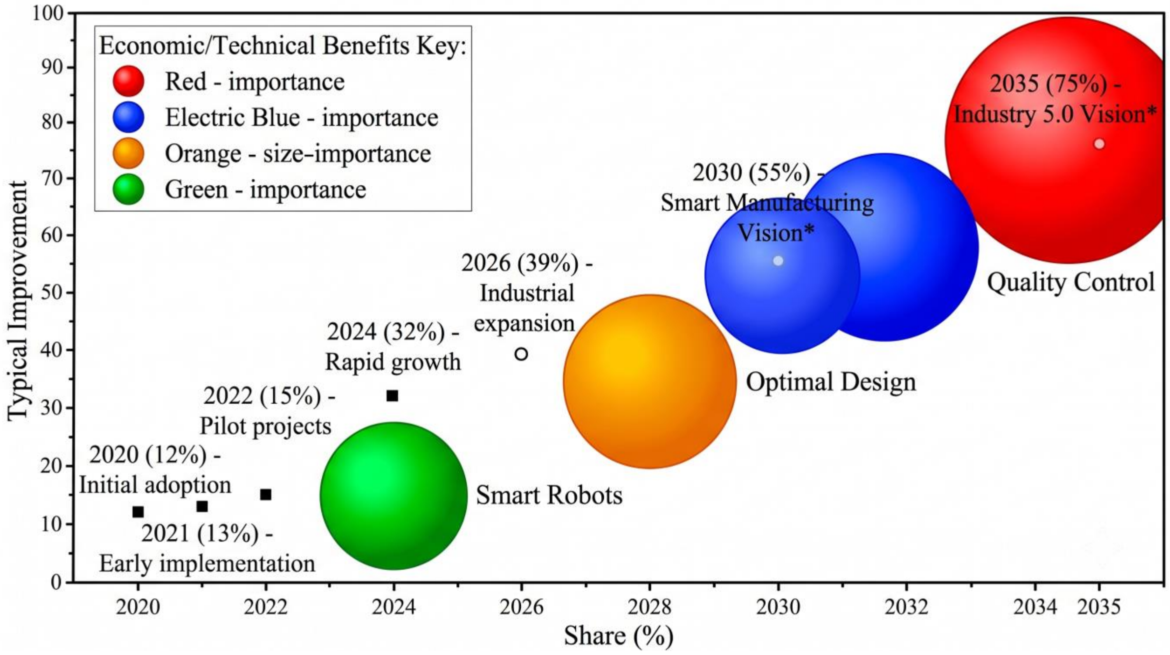

Figure 2: AI-Based Vision System Architecture and Data Flow

Unlike the human eye, which is prone to fatigue and errors after a few hours of work, the AI system operates continuously at a scanning rate of hundreds of products per minute, detecting micro-defects such as scratches, casting porosity, hairline cracks, or geometric tolerance deviations at the micrometer level with absolute precision [2, 9]. At the same time, in mechanical manufacturing facilities-where the risk of workplace accidents is high-AI cameras serve as automated safety supervisors. The algorithm continuously identifies and analyzes worker behavior, issuing warning signals or immediately triggering an emergency machine shutdown if it detects serious violations such as failing to wear safety goggles in the welding shop, failing to wear a safety helmet in the operational area of a hydraulic press, or stepping into the robot arm's exclusion zone [10].

3.4. Methodology of Predictive Maintenance Based on Mathematical AI

One of the most valuable contributions of AI in mechanical systems engineering, both academically and practically, is the transformation of equipment maintenance models. Reactive maintenance (repairing only after a failure occurs) causes significant downtime losses for factories due to sudden production line stoppages. Preventive Maintenance (scheduled maintenance) has the drawback of wasting costs and components by replacing parts that are still functioning reliably. The AI-based Predictive Maintenance (PdM) solution thoroughly addresses this issue through the Condition-based Monitoring methodology [1].

Through vibration sensors, infrared temperature sensors mounted on the main spindle bearings of CNC machines, and servo motor current sensors, time-series data is continuously collected [2]. Advanced signal processing algorithms (such as the Wavelet transform) combined with Long Short-Term Memory (LSTM) neural networks analyze distinctive frequency characteristics. The AI system is capable of early detection of potential failure indicators-such as cutting tool tooth wear, shaft misalignment, or reduced coil insulation-weeks before a catastrophic mechanical failure occurs [4]. This helps businesses reduce maintenance costs by up to 30% and cut unplanned downtime by half [7, 8].

Table 1: Summary of Key AI Adoption Barriers in Vietnam's Mechanical Engineering Sector

Barrier	2022 - Initial Analysis	2023 - Survey	2024 - Progress Tracking	2025 - Assessment
Investment Cost	42%	High	Medium	High
Digital Data	31%	Medium	High	Medium
Human Resources	27%	Medium	Medium	Moderate

3.5. Adaptive Automation Using Robots and Optimization of Production Economics

The combination of AI and precision engineering has led to a quantum leap from "hard automation" to "adaptive automation." New-generation CNC machines equipped with machine learning algorithms can automatically adjust process parameters-such as cutting speed, feed rate, and cutting depth-during machining to adapt to variations in workpiece hardness or tool wear, thereby maximizing machining cycle efficiency and surface finish [9, 10]. At the same time, industrial robots and autonomous mobile robots (AGVs/AMRs) equipped with Simultaneous Localization and Mapping (SLAM) algorithms and reinforcement learning can autonomously plan flexible paths within the factory without the need for fixed rails, enabling the creation of highly customizable factory layouts tailored to specific product modules [1, 5, 6].

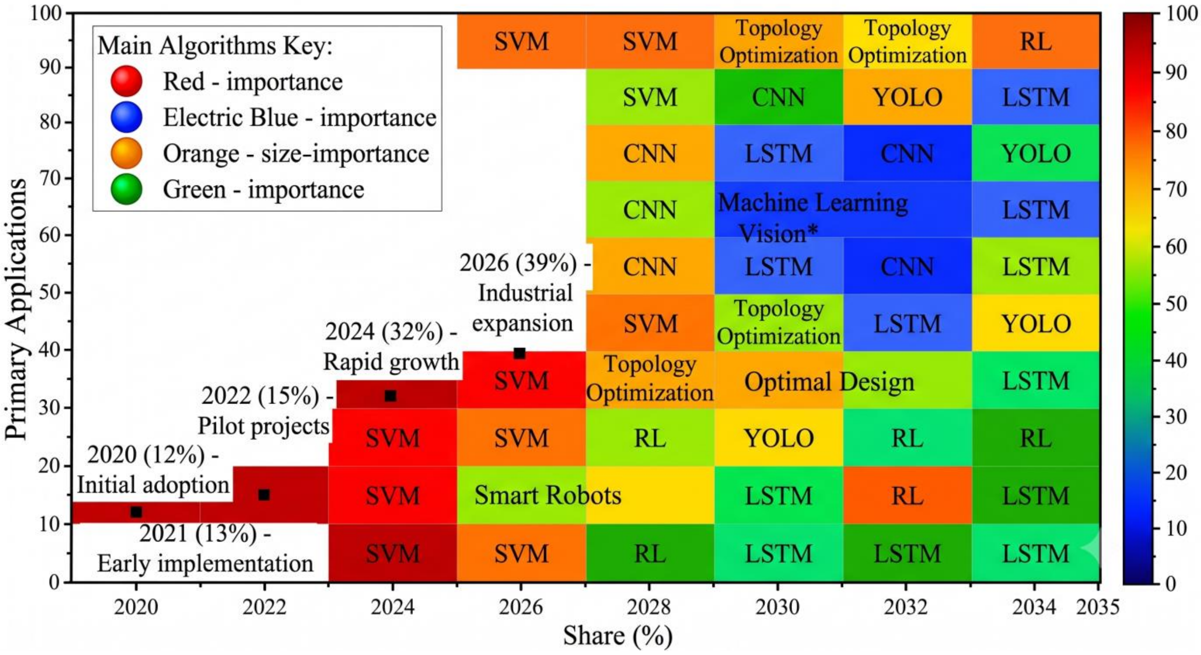

Figure 3: AI Application Sectors and Core Barriers in Vietnam

At the cost management level, AI provides strong support for solving complex production economics problems. By applying time-series models to analyze big data from the raw material supply market, AI can forecast price fluctuation trends for base metal raw materials-such as steel billets or aluminum sheets-with very low error margins [4]. This helps the planning department make optimal procurement decisions and mitigate the risk of price volatility. Furthermore, flat-sheet nesting algorithms help reduce scrap rates during laser cutting, thereby maximizing the plant's material utilization rate [8].

Table 2: Classification of Key Factors and Enabling Solutions

Key Factor	Priority Level / Solution	Description
Investment Cost	High Barrier (42%)	Largest obstacle, especially for SMEs.
Digital Data	Medium/High Barrier (31%)	Lack of digitized data; difficulties in data collection and processing.
Human Resources	Medium Barrier (27%)	Critical shortage of interdisciplinary engineers (AI + Mechanical).
Enabling Solutions	General & Specific	Support mechanisms from policy and training initiatives.

The analysis highlights a key fact: the computer vision-based quality inspection sector is currently the top destination for investment capital due to its rapid return on investment (short ROI) and the mandatory requirement for defect control from global component export partners [2, 3, 7].

4. CONCLUSION

Artificial Intelligence has convincingly demonstrated that it is no longer just a fleeting technological trend, but rather a comprehensive methodological shift that is reshaping the future of the mechanical engineering industry in Vietnam. The integration of intelligent mathematical solutions-from material-optimized generative design and real-time quality control via computer vision to “zero downtime” predictive maintenance models-has brought about breakthrough improvements in labor productivity, the quality of engineering products, and the ability to participate in the global value chain.

However, from the perspectives of academic research and industrial management, this development in Vietnam is revealing systemic imbalances. Most of this successful transformation remains confined to large enterprises or foreign-invested enterprises (FIEs) with abundant financial resources, while small and medium-sized enterprises (SMEs)-the backbone of the industry, accounting for over 95% of all businesses-are falling into the trap of technological backwardness due to their inability to overcome barriers related to investment capital, the inadequacy of rudimentary data infrastructure, and, in particular, the severe shortage of interdisciplinary human resources [10]. To resolve these strategic bottlenecks, the Council of Professors and research experts propose a systematic, nationally coordinated action framework:

- Regarding the Government and Macro-Management Agencies: It is necessary to urgently develop and promulgate a system of national technical standards for industrial data structures, IIoT device connectivity, and cybersecurity in smart manufacturing environments. It is necessary to establish dedicated funds to finance technological innovation and implement tax incentive mechanisms at the maximum allowable level or provide interest rate subsidies on long-term loans for domestic mechanical engineering enterprises investing in the purchase of new-generation CNC machines with built-in digital infrastructure and AI software.

- For Universities and Technology Institutes: A thorough overhaul of the curriculum framework for training mechanical engineering students is required. The outdated model of purely mechanical engineering education must be completely transitioned to an advanced mechatronics model integrated with digital technology. Curriculum modules on data structure programming (Python), applied mathematics in machine learning, the Industrial Internet of Things (IIoT), and smart sensor signal processing must be standardized as required courses in high-quality engineering programs.

- As for domestic mechanical engineering companies themselves: They need to proactively move away from the traditional, ad-hoc approach to workshop management and establish a long-term strategic vision for digital transformation that aligns with their core financial capabilities. Companies should not rush to invest in expensive AI systems before preparing the necessary infrastructure; the optimal approach is to standardize technical processes and digitize all raw data-including machine logs and cutting parameters-to create clean data repositories, which will serve as the foundation for the success or failure of future AI algorithm training. Strengthening strategic alliances with universities to commission research and with domestic software solution providers will help optimize investment costs and ensure sustainable mastery of the technology.

- The findings indicate that the Vietnamese mechanical manufacturing industry is undergoing a profound transition from conventional analytical and experimental approaches toward intelligent, data-driven engineering based on Big Data analytics, machine learning, and digital simulation. AI has become a key enabling technology across the entire manufacturing value chain, ranging from nonlinear structural optimization and deep-learning-based defect detection to adaptive robotic motion planning and intelligent production systems.

Despite these promising developments, the study identifies three major challenges that continue to hinder widespread AI implementation in Vietnam's mechanical engineering industry:

+ Limited availability of high-quality industrial datasets;

+ A severe shortage of interdisciplinary professionals possessing expertise in both mechanical engineering and artificial intelligence; and substantial investment costs that remain prohibitive for small and medium-sized manufacturing enterprises (SMEs).

Based on these findings, the paper proposes strategic recommendations concerning governmental policies, interdisciplinary engineering education, industrial digital transformation, and collaborative innovation frameworks aimed at accelerating AI adoption while strengthening Vietnam's technological independence in advanced manufacturing.

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