Engineering Frontiers
Vol. 1, No. 3, 2025 29
Review

Applications of Artificial Intelligence in Engineering: Current Status, Challenges, and Future Perspectives

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Abstract
The rapid development of artificial intelligence (AI) has profoundly transformed the paradigm of modern engineering. This paper systematically reviews the current applications of AI in core engineering fields, including civil, mechanical, electrical, and chemical engineering, and analyzes the implementation paths of key technologies such as machine learning, deep learning, and reinforcement learning. By summarizing typical scenarios including intelligent design optimization, predictive maintenance, quality control, and autonomous decision-making, this study reveals the mechanism by which AI empowers engineering practices. Meanwhile, major challenges are thoroughly discussed, including data acquisition and quality, model interpretability, cross-domain generalization, and engineering ethics. Future prospects are also proposed for the deep integration of AI and engineering disciplines. This review aims to provide comprehensive theoretical references and practical guidance for researchers and engineers engaged in AI-driven engineering applications.
Keywords: Artificial Intelligence; Engineering Applications; Machine Learning; Deep Learning; Intelligent Manufacturing; Predictive Maintenance

1. Introduction

1.1 Research Background and Significance

The history of human engineering practice is a chronicle of continuous pursuit of efficiency improvement and innovative breakthroughs(Rizzo, 2025). From the first industrial revolution driven by steam engines to the second industrial revolution dominated by electrification, from the third industrial revolution led by information technology to the current fourth industrial revolution characterized by intelligence, each technological paradigm shift has brought fundamental changes to the engineering field(Rijwani et al., 2025). Against this macro background, the rise of artificial intelligence technology is penetrating all aspects of engineering practice with unprecedented depth and breadth, giving birth to intelligent engineering as a new interdisciplinary field(Palazzo et al., 2025). Since the concept of artificial intelligence was proposed in the 1950s, it has experienced multiple waves of development and troughs(Negnevitsky, 2025). In recent years, benefiting from the exponential growth of computing power, the continuous accumulation of massive data, and major breakthroughs in algorithmic theory, artificial intelligence technology has achieved a leapfrog transformation from laboratory research to engineering applications(Xu et al., 2025). In particular, the maturation of deep learning technology enables machines to automatically extract high-level features from complex unstructured data, a capability that has natural adaptability advantages for handling the high-dimensional, nonlinear, and uncertain problems commonly found in the engineering field(Khan, 2025; Zekang et al., 2025). Figure 1 presents the overall technical framework of artificial intelligence applications in the engineering field. From Figure 1a, it can be clearly seen that the core technology layer contains three major pillars: machine learning, deep learning, and reinforcement learning. Figure 1b shows the radiation paths of these technologies to the four major engineering domains of civil, mechanical, electrical, and chemical engineering, while Figure 1c further details the typical application scenarios in each domain.

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https://doi.org/10.71411/ef.2025.v1i3.1379

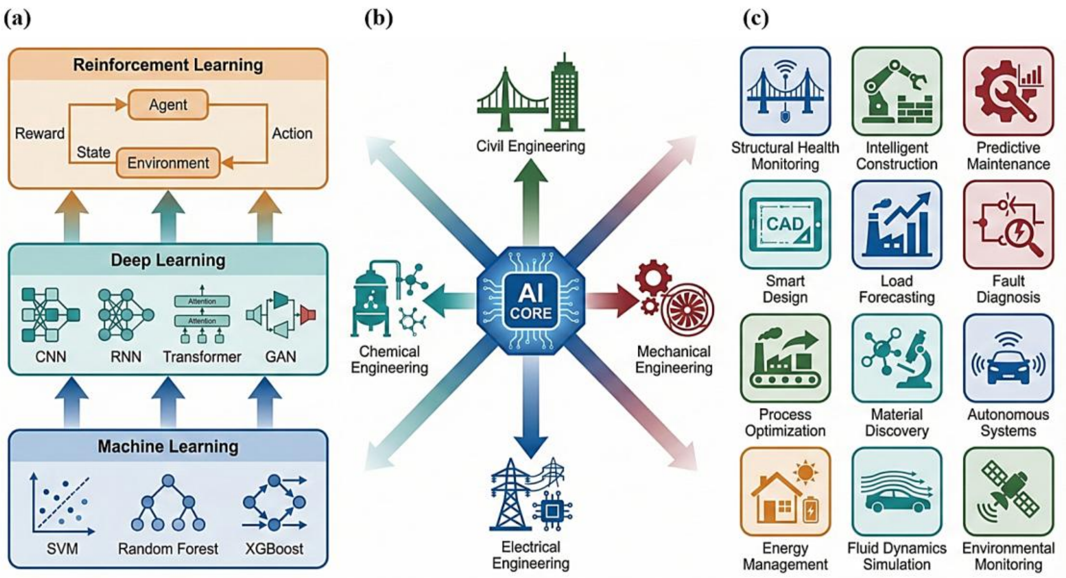

Figure 1. Technical Framework of AI Applications in Engineering: (a) core technology layer architecture, (b) technology radiation paths to engineering domains, (c) typical application scenarios in each domain.

The intrinsic driving forces for introducing artificial intelligence technology in the engineering field stem from multiple dimensions(Alghazo et al., 2025). First, the complexity of modern engineering systems continues to escalate, and traditional physics-based analytical methods often fall short when facing problems involving multi-physics coupling, multi-scale interactions, and dynamic evolution, while data-driven artificial intelligence methods can effectively break through this bottleneck(Wang et al., 2025). Second, the massive monitoring data accumulated in engineering practice has long been in a state of insufficient value mining, and artificial intelligence technology provides a systematic methodology for realizing the transformation from data to knowledge and then to decision-making(Palazzo et al., 2025). Third, the demand for multi-objective collaborative optimization of safety, reliability, and economy in the engineering field is increasingly urgent, and the powerful optimization capabilities of artificial intelligence precisely meet this demand(Chen et al., 2025). Finally, the continuous rise in labor costs and the relative shortage of technical talents are also objectively driving the accelerated implementation of intelligent technologies(Xue et al., 2025).

From a global perspective, major industrialized countries have elevated the integrated development of artificial intelligence and engineering to the national strategic level(Demaidi, 2025). The United States' Advanced Manufacturing National Strategic Plan, Germany's Industry 4.0 strategy, China's Made in China 2025 initiative, and Japan's Society 5.0 vision all position artificial intelligence as the core engine driving the transformation and upgrading of the engineering field(Hu et al., 2025). Research investment from academia and industry also shows explosive growth, with the number of related paper publications and patent applications maintaining an annual growth rate exceeding 30 percent(Gradinaru et al., 2025). Table 1 summarizes a comparative analysis of research intensity and application maturity of artificial intelligence in major engineering domains in recent years. It can be observed that directions such as structural health monitoring, intelligent manufacturing, and energy management have entered the stage of large-scale application, while frontier directions such as autonomous design and cognitive construction are still in the exploration period.

Table 1 Comparison of Research Intensity and Application Maturity of AI in Major Engineering Domains

Domain	Application Direction	Research Intensity	Maturity	Representative Technologies

https://doi.org/10.71411/ef.2025.v1i3.1379

Civil	Structural Health Monitoring	High	Mature	CNN, RNN
Civil	Smart Construction Mgmt	Med-High	Growth	Computer Vision, NLP
Mechanical	Predictive Maintenance	High	Mature	LSTM, Transfer Learning
Mechanical	Intelligent Design Optim	Med-High	Growth	GAN, RL
Electrical	Grid Load Forecasting	High	Mature	Ensemble Learning, DL
Chemical	Process Optimization	Medium	Growth	Deep RL, MPC

2 Key Technologies and Methods

2.1 Machine Learning Fundamentals

Machine learning, as a core branch of artificial intelligence, essentially learns patterns from data through algorithms to make predictions or decisions(Kazi, 2025). According to different learning paradigms, machine learning can be divided into three major categories: supervised learning, unsupervised learning, and reinforcement learning(Morales & Escalante, 2022). As shown in Figure 2a, these three learning paradigms have different data requirements and application scenarios. Supervised learning relies on labeled data for model training and is suitable for classification and regression problems(Tiwari, 2022). Unsupervised learning aims to discover the intrinsic structure of data and is commonly used for clustering and dimensionality reduction tasks(Tripathy et al., 2021). Reinforcement learning obtains feedback signals through interaction with the environment and is suitable for sequential decision problems. Figure 2b presents the classification system of commonly used machine learning algorithms, covering major categories including linear models, tree models, kernel methods, ensemble methods, and neural networks(Luo et al., 2025).

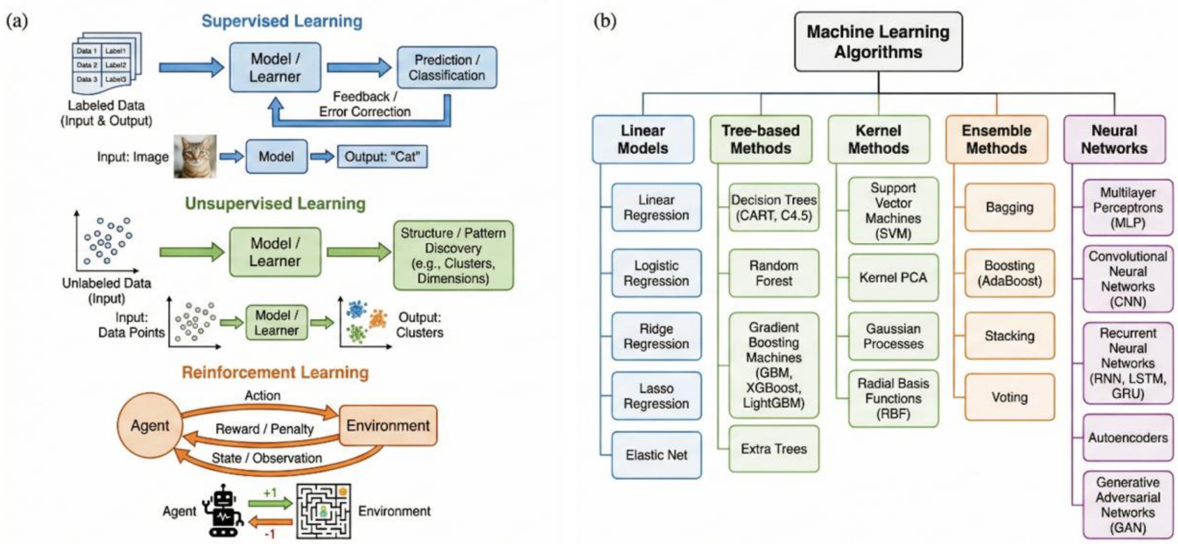

Figure 2. Hierarchical Architecture of Key AI Technologies: (a) fundamental algorithm layer composition, (b) model training and optimization workflow, (c) deployment architecture for engineering applications.

Under the supervised learning framework, the goal of model training is to minimize the difference between predicted values and true values(Tiwari, 2022). Given a training dataset containing N samples, where each sample consists of an input feature vector x and a target variable y, the estimation of model parameters can be achieved by minimizing the empirical risk function(Montanari & Saeed, 2022). The loss function L measures the prediction error of individual samples(Barendse & Patton, 2022). For regression problems, mean squared error loss is commonly used; for classification problems, cross-entropy loss is typically employed. The regularization term is used to constrain model complexity to prevent overfitting. The regularization strength coefficient needs to be tuned through methods such as cross-validation.

Support vector machines are widely applied machine learning methods in the engineering field(Pisner & Schnyer, 2020). For binary classification problems, support vector machines achieve class separation by finding the maximum margin hyperplane(Valkenborg et al., 2023). The introduction of kernel functions enables support vector machines to construct nonlinear decision boundaries in high-dimensional feature spaces while avoiding explicit computation of high-dimensional feature mappings(Du et al., 2024). Ensemble learning improves prediction performance by combining multiple base learners and is an effective strategy for handling complex engineering problems. Random forests, as a typical bagging ensemble method, construct multiple decision trees through bootstrap sampling of training data, with final predictions determined by voting or averaging across trees.

2.2 Deep Learning Architectures

Deep learning is an important development direction of machine learning, with its core characteristic being the use of multi-layer neural networks for hierarchical feature representation learning(Chen & Chen, 2026). Unlike traditional machine learning methods that require manually designed features, deep learning can automatically extract multi-scale, multi-level abstract features from raw data. This capability performs particularly well when processing unstructured data such as images, speech, and text.

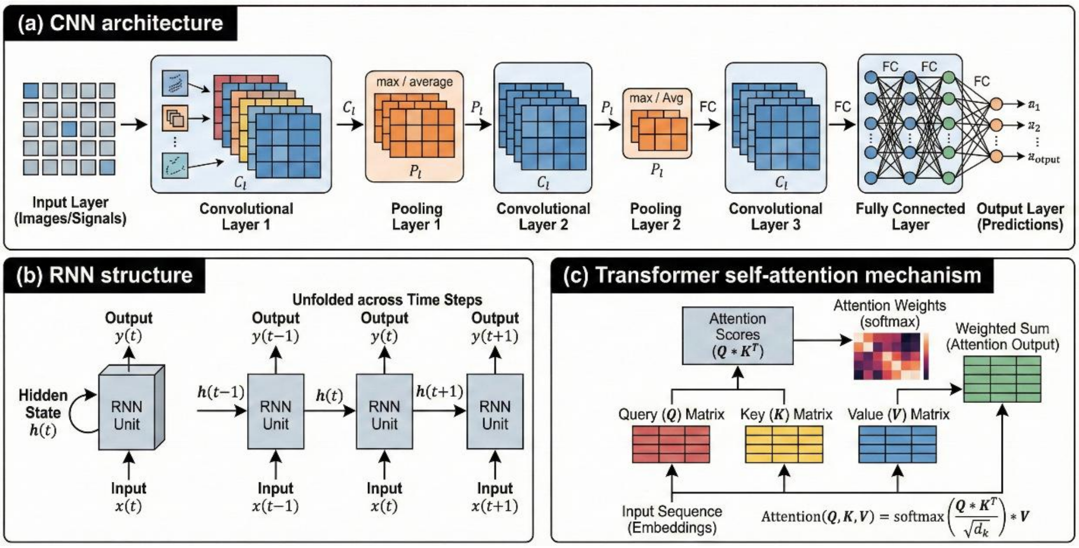

Figure 3. AI-Driven Structural Health Monitoring System: (a) multi-source sensor data fusion process, (b) deep learning-based damage identification model architecture, (c) bridge structure monitoring deployment scheme.

Convolutional neural networks are specialized architectures for processing grid-structured data and are widely used in engineering image analysis(Knyaz et al., 2020). Convolution operations achieve translation-invariant feature extraction through local receptive fields and weight sharing. As shown in Figure 3a, typical convolutional neural networks are stacked with convolutional layers, pooling layers, and fully connected layers, forming hierarchical representations from low-level features to high-level semantics. Figure 3b shows the structure of recurrent neural networks, which model sequential data through recurrent connections of hidden states. Figure 3c presents the self-attention mechanism of Transformer architecture, which processes global dependencies through parallel computation, overcoming the limitations of recurrent networks in handling long sequences(Soydaner, 2022).

2.3 Reinforcement Learning

Reinforcement learning is a learning paradigm for solving sequential decision problems. The core idea is that an agent improves its policy by continuously interacting with the environment and obtaining reward signals to achieve cumulative reward maximization(Zhang et al., 2021). Reinforcement learning is particularly suitable for optimization and control problems in engineering

https://doi.org/10.71411/ef.2025.v1i3.1379

systems, such as robot path planning, process parameter optimization, and energy management. The Markov decision process provides a mathematical framework for describing reinforcement learning problems, including states, actions, state transition probabilities, and reward functions. Deep reinforcement learning combines deep neural networks with reinforcement learning, using neural networks to approximate value functions or policies, enabling handling of high-dimensional state spaces(Giannakopoulos et al., 2021).

3 Engineering Applications

3.1 Civil Engineering

In the field of civil engineering, structural health monitoring is one of the most mature application directions for artificial intelligence technology. Modern infrastructure such as bridges, tunnels, and high-rise buildings are equipped with large numbers of sensors, generating massive vibration, strain, and displacement monitoring data. Deep learning technology can effectively identify damage features from this multi-source heterogeneous data, achieving early warning of structural damage(LeCun et al., 2015). Convolutional neural networks excel at processing one-dimensional vibration signal data, automatically learning frequency domain features and time-frequency features(Hakim et al., 2022). Recurrent neural networks and their variants are particularly suitable for capturing long-term dependencies in time series data, enabling remaining life prediction of structures.

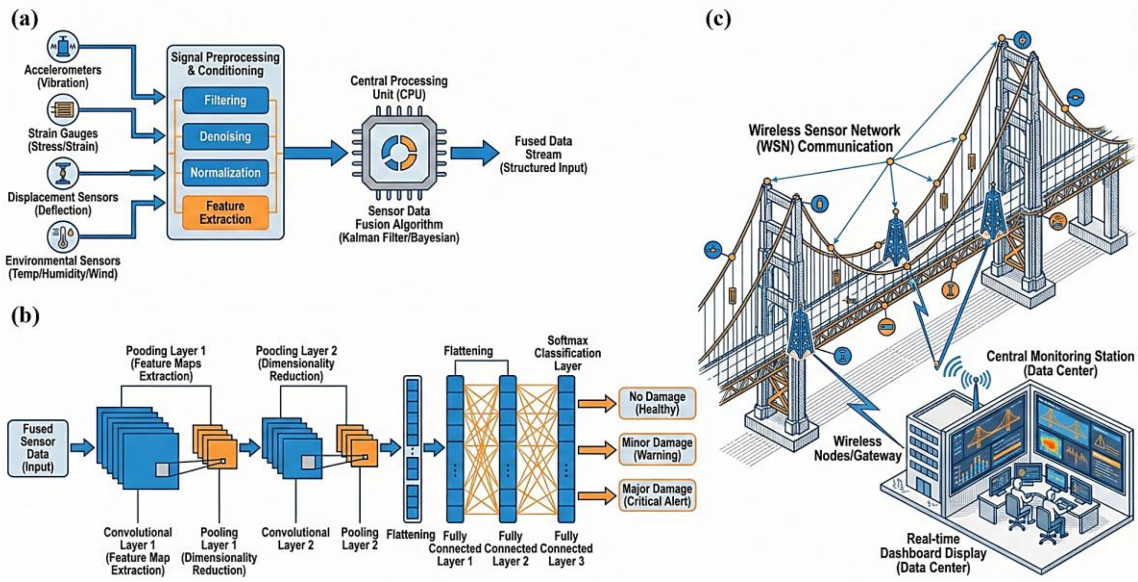

Figure 4. AI-Driven Predictive Maintenance System: (a) multi-sensor data acquisition architecture for industrial equipment, (b) remaining useful life prediction model, (c) predictive maintenance decision support workflow.

As shown in Figure 4a, artificial intelligence-driven structural health monitoring systems achieve comprehensive perception of structural states through multi-source sensor data fusion. Figure 4b presents a typical deep learning model architecture for damage identification, including data preprocessing modules, feature extraction networks, and classification output layers. Figure 4c shows a bridge structure monitoring deployment scheme, achieving real-time acquisition and intelligent analysis of structural response data through wireless sensor networks and edge computing devices(Zhang et al., 2024).

3.2 Mechanical Engineering

Predictive maintenance is the most successful application of artificial intelligence in the mechanical engineering field. Traditional reactive maintenance and time-based preventive maintenance either lead to unexpected downtime or cause excessive maintenance costs(Yazdi, 2024). Predictive maintenance based on condition monitoring and artificial intelligence can accurately predict equipment failure time, achieving optimal maintenance strategy formulation. Long short-term

https://doi.org/10.71411/ef.2025.v1i3.1379

memory networks perform excellently in remaining useful life prediction tasks, effectively capturing degradation trends in equipment condition through their unique gating mechanisms(Zhang et al., 2018).
As shown in Figure 5a, industrial equipment multi-sensor data acquisition architectures typically include multiple types of sensors such as vibration, temperature, current, and oil analysis, with data streams flowing to edge computing devices for preprocessing. Figure 5b presents a remaining useful life prediction model architecture based on deep learning, showing the process from time series input through encoder layers, attention mechanisms, and decoders to life output. Figure 5c shows the complete process of predictive maintenance decision support systems, from data collection and anomaly detection to fault diagnosis, remaining life prediction, and maintenance scheduling, forming a closed-loop intelligent maintenance system.

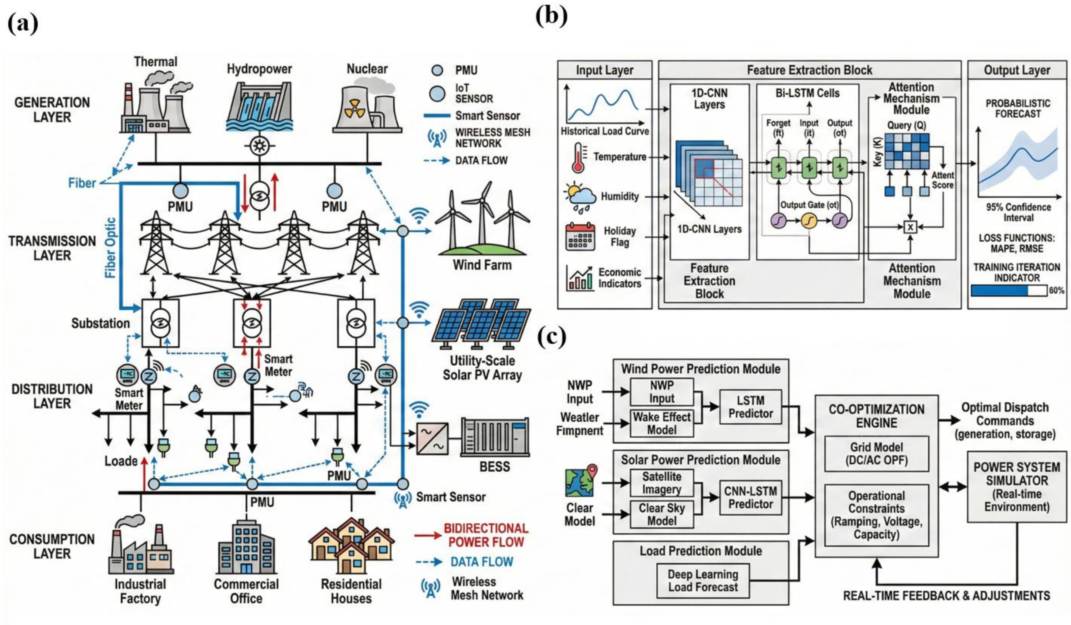

Figure 5. AI Applications in Power Systems: (a) smart grid overall architecture, (b) deep learning model for power load forecasting, (c) renewable energy power prediction and dispatch coordination optimization framework.

3.3 Electrical Engineering
Load forecasting of power systems is a typical time series prediction problem, and the accuracy of forecasting directly affects power grid dispatching decisions and operational efficiency. The multi-factor influence characteristics of power load, including historical load patterns, meteorological conditions, calendar effects, and social activity factors, make traditional statistical methods difficult to capture complex nonlinear relationships(Cheng et al., 2021). Deep learning models perform excellently in load forecasting tasks by automatically learning complex interaction features of multiple input variables. The attention mechanism enables models to dynamically focus on the most influential time points and feature dimensions, further improving forecasting accuracy.
With the large-scale integration of renewable energy sources such as wind and solar power, the uncertainty of new energy output has become a major challenge for power grid operation. Artificial intelligence technology plays a key role in new energy power forecasting, grid stability analysis, and dispatching optimization. Graph neural networks are particularly suitable for power system analysis due to their ability to capture the topological structure of power grids while considering node and edge features(Liao et al., 2021).

3.4 Chemical Engineering
Chemical engineering processes typically involve complex reaction kinetics, heat and mass transfer phenomena, and multi-variable coupling characteristics(Csendes et al., 2023). Traditional mechanism

https://doi.org/10.71411/ef.2025.v1i3.1379

modeling methods have limitations in computational cost and accuracy for complex multi-phase reaction systems. Hybrid models combining data-driven artificial intelligence methods with mechanism-based models have become an important research direction. By embedding physical constraints into neural network structures, the generalization ability and interpretability of models can be enhanced(Lin et al., 2025).

Accelerated discovery of new materials is another application highlight of artificial intelligence in the chemical engineering field. Traditional trial-and-error experimental methods are extremely time-consuming and costly in the vast material composition and structure space. Machine learning methods can establish mappings from material structures to properties, enabling rapid screening of candidate materials. Active learning strategies further improve exploration efficiency by intelligently selecting the most informative experiments(Dimitriadou et al., 2016).

4 Challenges and Strategies

Despite the remarkable achievements of artificial intelligence technology in the engineering field, practical applications still face multi-level challenges. Data scarcity and quality issues are among the most common challenges. In many engineering scenarios, failure events are rare, leading to a lack of labeled samples for model training(Alzubaidi et al., 2023). Additionally, the noise, missing values, and inconsistencies in engineering data also affect model performance. Transfer learning and few-shot learning techniques provide feasible solutions for addressing data scarcity issues. By utilizing knowledge learned from related domains or tasks, the data requirements for new tasks can be significantly reduced.

Table 2 Summary of Key Challenges and Technical Solutions.

Challenge Category	Specific Manifestations	Technical Solutions
Data Scarcity	Rare fault samples, insufficient labeled data	Transfer learning, few-shot learning, data augmentation
Interpretability	Black-box decision logic, trust deficit	Explainable AI, attention visualization, SHAP
Cross-domain Transfer	Poor generalization across equipment types	Domain adaptation, meta-learning
Computing Resources	Edge deployment constraints, real-time requirements	Model compression, edge AI, knowledge distillation

Model interpretability issues are a major barrier to the application of artificial intelligence in safety-critical engineering domains. Deep learning models are often considered black boxes, and their complex nonlinear transformations make it difficult to explain the basis of prediction results(Guidotti et al., 2018). Explainable artificial intelligence research is committed to developing methods that can reveal model decision logic, including attention visualization, feature importance analysis, and local interpretation techniques. Building trust in artificial intelligence systems requires progress in both technical interpretability and regulatory compliance certification.

Cross-domain transfer issues limit the reusability of artificial intelligence models. Models trained on specific equipment or working conditions often experience significant performance degradation when applied to new environments. This is because the statistical characteristics of data distributions differ across domains. Domain adaptation techniques reduce distribution differences between source and target domains by learning domain-invariant feature representations. Meta-learning provides another perspective for solving this problem by learning to learn, enabling models to quickly adapt to new tasks(Vettoruzzo et al., 2024).

As shown in Figure 6a, the hierarchical division of challenges and their association mechanisms show interconnections and mutual influences across different levels. Figure 6b presents a solution matrix matching each challenge category with corresponding technical approaches. Figure 6c depicts the technology evolution roadmap, showing the progression of applications from current state through near-term to long-term future.

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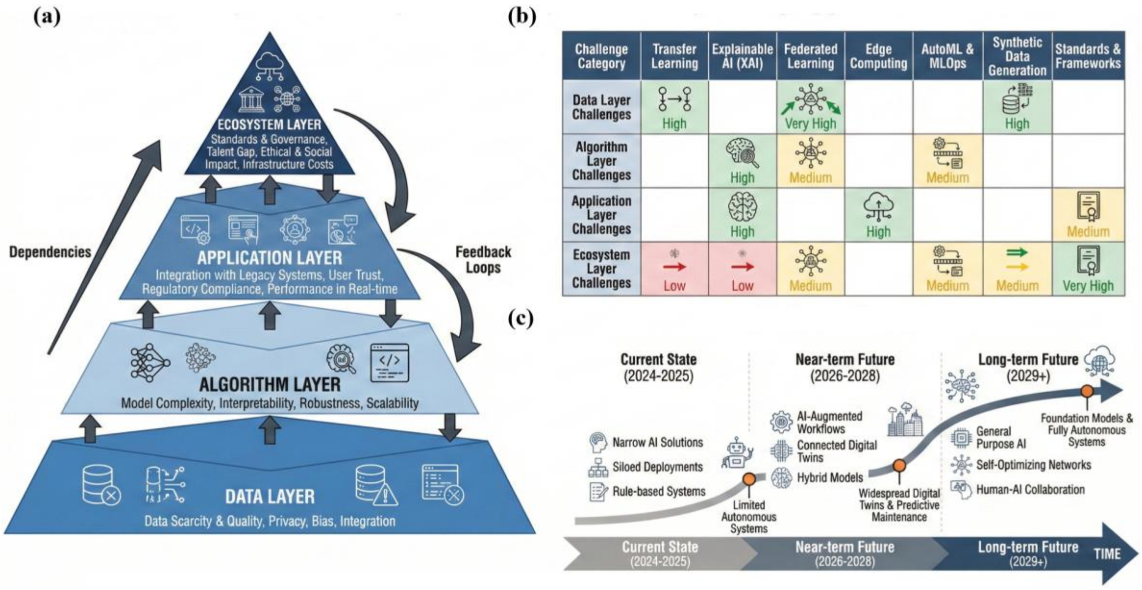

Figure 6. Challenges and Strategies for AI Engineering Applications: (a) hierarchical challenge classification and correlation mechanisms, (b) technical solutions for each challenge category, (c) technology evolution roadmap.

Engineering ethics and liability attribution issues are becoming increasingly prominent as artificial intelligence plays an increasingly important role in critical engineering decisions. When recommendations or decisions from artificial intelligence systems lead to engineering accidents, how responsibility should be defined and allocated remains an unresolved issue. Algorithmic fairness and bias issues in artificial intelligence decisions also exist in the engineering field. Establishing ethical guidelines and regulatory frameworks for artificial intelligence engineering applications is a necessary condition for ensuring the healthy development of the technology.

5 Future Perspectives

Looking ahead, the integration of artificial intelligence and engineering will present deeper and broader development trends. Multi-modal data fusion and perception is an important development direction. Comprehensive perception of engineering systems requires integrating multi-modal data from different types of sensors, including images, vibration, sound, temperature, and chemical composition. Advances in multi-modal deep learning technology will make it possible to extract unified feature representations from these heterogeneous data, enabling more comprehensive and accurate perception of engineering system states.

Deep integration of digital twins and artificial intelligence will reshape the management paradigm of engineering systems. Digital twins achieve real-time monitoring, predictive analysis, and optimization decisions by establishing high-fidelity virtual mirrors of physical systems. Artificial intelligence technology plays a core role in digital twins, including sensor data-based model calibration, anomaly detection and diagnosis, future state prediction, and optimization recommendation generation. As Internet of Things technology becomes more prevalent and computing power improves, digital twins will extend from individual equipment to complex engineering systems and even entire infrastructure networks.

The development of autonomous engineering systems represents the advanced form of artificial intelligence and engineering integration. From assisted decision-making to autonomous decision-making, the role of artificial intelligence in engineering systems is undergoing fundamental transformation. Autonomous construction robots can independently complete tasks such as masonry, welding, and painting at complex construction sites. Autonomous inspection systems can perform regular unmanned inspections of infrastructure and automatically generate inspection reports. However, the high safety requirements of engineering systems mean that achieving full autonomy will be a gradual process, and human-machine collaboration will maintain a dominant position for a considerable period.

Foundation models in the engineering domain represent another noteworthy trend. The powerful generalization capabilities and few-shot learning abilities demonstrated by large language models and multi-modal foundation models bring new possibilities for artificial intelligence applications in the engineering field(Shao & Zhang, 2025). Through continued pre-training and task-specific fine-tuning on professional corpora such as engineering literature, specification standards, and design documents, domain foundation models with engineering expertise can potentially be obtained. Such models have broad application prospects in scenarios such as engineering knowledge question-answering, design assistance, and report generation.

6 Conclusion

Artificial intelligence technology is penetrating every aspect of engineering practice with unprecedented depth and breadth, driving a paradigm shift in the engineering field from experience-driven to data-driven, and from manual decision-making to intelligent decision-making. This paper systematically reviews the application status of artificial intelligence in core engineering domains including civil engineering, mechanical engineering, electrical engineering, and chemical engineering, and provides detailed analysis of the engineering implementation pathways and applicable characteristics of key technologies such as machine learning, deep learning, and reinforcement learning.

From an application perspective, directions such as structural health monitoring, predictive maintenance, power load forecasting, and chemical process optimization have developed to a relatively mature stage and are beginning to enter the track of large-scale application. Frontier directions such as intelligent design, autonomous construction, and new material discovery are in a rapid development period, showing great application potential. From a technical perspective, deep learning technology demonstrates excellent performance in engineering data analysis tasks but still has obvious shortcomings in interpretability, generalization capability, and few-shot learning. Technical routes such as physics-informed integration, transfer learning, and explainable artificial intelligence provide effective approaches for addressing these challenges.

Currently, the application of artificial intelligence in the engineering field still faces multi-level challenges including data scarcity, insufficient model interpretability, difficulties in cross-domain transfer, limited computing resources, and the absence of engineering ethics norms. The systematic resolution of these challenges requires the coordinated advancement of technological innovation, standards construction, talent cultivation, and ecosystem building. Looking ahead, multi-modal perception fusion, deep application of digital twins, development of autonomous engineering systems, and construction of engineering domain foundation models will become important development directions, promising to advance the integration of artificial intelligence and engineering to a higher level.

This review aims to provide comprehensive technical references for researchers and practitioners in the engineering field, helping them grasp the development trajectory of artificial intelligence engineering applications, identify key technical challenges and opportunities, and thereby make wiser research planning and technical decisions in this rapidly evolving field. The deep integration of artificial intelligence and engineering is a long-term evolutionary process that requires sustained investment and concerted efforts from academia, industry, and government departments to jointly promote the intelligent transformation and upgrading of the engineering field.

Funding

This work was supported without any funding.

Data Availability

If necessary, it can be provided. If necessary, it can be provided.

Competing Interests

The authors declare no competing interests.

Acknowledgments

We thank Google AI for image generation support.

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