

Artificial Intelligence for Engineering Solutions: Trends, Challenges, and Future Directions

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1. Introduction

Artificial intelligence (AI) is now a fundamental tool in the development of engineering solutions for prediction, diagnosis, optimization, monitoring, control, and decision support [1]. Its application has broadened to encompass industrial systems, energy networks, infrastructure, transportation, manufacturing, embedded systems, and environmental domains [2]. This evolution represents a significant transition: artificial intelligence is increasingly integrated within engineering systems that interact with physical processes, operational constraints, and real-time data, rather than being employed solely as an isolated modeling technique [3].

This transition is evident in recent research that combines learning models with sensors, digital platforms, optimization methods, image processing, fault detection, time-series forecasting, and decision-making tools [4]. The integration of these components addresses the complexity of engineering problems, which seldom depend on a single variable or objective. Engineering solutions typically require balancing cost, reliability, safety, energy consumption, environmental impact, computational efficiency, and implementation feasibility [5]. In this context, predictive accuracy is considered alongside other performance criteria, including traceability, operational integration, and deployment capability [6].

Figure 1 displays a bibliometric keyword co-occurrence network constructed from Scopus-indexed research articles published in English between 2020 and 2026 on AI applications in engineering solutions. The network was generated using VOSviewer (version 1.6.21), employing author keywords, full counting, thesaurus-based normalization, and a minimum threshold of five occurrences. The resulting network comprises 72 terms organized into eight clusters. The nodes with the highest occurrence and total link strength are deep learning, machine learning, AI, predictive maintenance, digital twin, computer vision, and fault diagnosis.

This distribution demonstrates that AI in engineering is progressing not as a uniform field, but as a collection of interconnected lines defined by shared technical functions [2]. The first notable pattern is the centrality of deep learning and computer vision models, which are associated with inspection, segmentation, detection, and diagnosis [7]. This indicates that a significant portion of the field focuses on converting visual or spatial information into actionable evidence for evaluating physical systems [8]. The second pattern highlights the prominence of predictive maintenance, fault diagnosis, fault detection, and condition monitoring, which shift the focus from simple variable estimation to failure



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anticipation and operational continuity [9]. This trend illustrates that AI is increasingly utilized in tasks aimed at reducing uncertainty in maintenance and operational decisions, rather than solely for classification or prediction [10]. A third pattern emerges with the inclusion of digital twin, embedded systems, internet of things, and edge computing, reflecting the integration of AI models with monitoring infrastructures, sensors, and execution platforms situated near the physical process [2]. Finally, the linkage among smart grids, renewable energy, energy efficiency, and sustainability underscores that resource efficiency and the energy transition serve as cross-cutting application domains [5]. Collectively, the network suggests that the field's maturity relies less on isolated techniques and more on the ability to integrate prediction, diagnosis, monitoring, and optimization within engineering systems subject to concrete operational constraints [11].

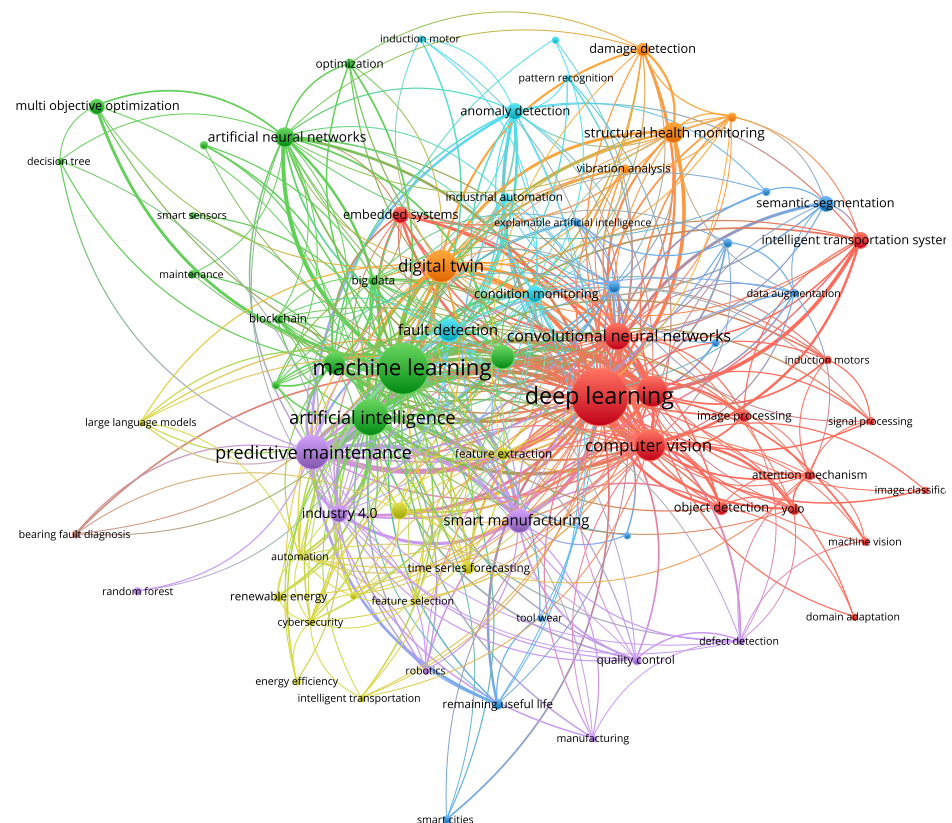


Figure 1. Bibliometric keyword co-occurrence network in Scopus-indexed literature on AI applied to engineering solutions, 2020–2026.

Based on this overview, the present article analyzes the trends, challenges, and perspectives of artificial intelligence in engineering solutions. The objective is to examine the integration of AI into engineering practice through models focused on prediction, diagnosis, monitoring, optimization, and decision-making [12]. The relevance of this analysis lies in its predictive accuracy, its ability to support reliable decisions, its ability to operate under real constraints, and its improvement of system performance and the development of sustainable, feasible solutions [5]. The next stage of the field will require explainable, robust, interoperable, and efficient models validated under real operating conditions [13].

2. Artificial Intelligence as an Integrative Approach in Engineering Solutions

Artificial intelligence is increasingly being used as a cross-cutting approach in engineering solutions rather than as an isolated computational technique. Recent studies show that AI methods are applied across infrastructure systems, manufacturing, energy

systems, smart grids, predictive maintenance, computer vision, and cyber-physical environments [1,3,9,14,15]. This broad use reflects a transition toward engineering frameworks where data, models, sensors, physical processes, and decision-making tools are integrated within the same operational context.

This integrative role is evident in areas such as predictive maintenance, digital twins, and computer vision. In predictive maintenance, AI supports data processing, fault diagnosis, remaining useful life estimation, and maintenance decision-making [9,14]. In digital twin applications, AI connects physical systems with virtual representations, data streams, simulation, monitoring, and optimization [3,15]. In computer vision, deep learning enables classification, object detection, semantic segmentation, inspection, and automated perception tasks in engineering workflows [16,17].

These trends indicate that the value of AI in engineering is not limited to predictive accuracy. Its relevance also lies in its capacity to support connected, adaptive, and operationally useful systems [18].

3. Prediction, Diagnostic Analysis, and Decision Support in Engineering Systems

Prediction, diagnosis, and decision support represent foundational applications of AI within engineering. In this context, machine learning and deep learning models enable the identification of patterns in operational data, facilitate fault detection, classify anomalous conditions, and anticipate component or system degradation prior to critical interruptions [4,10,12,19]. This focus is particularly significant in industrial, electrical, and mechanical domains, where reliability, operational continuity, and minimizing downtime are primary objectives.

Recent studies indicate that intelligent fault diagnosis has advanced from traditional signal-based techniques to methods that incorporate machine learning, transfer learning, deep learning, data fusion, and remaining useful life estimation [10,12,20]. These advanced approaches convert sensor data, including vibration, temperature, current, pressure, and dynamic behavior, into actionable information for predictive maintenance and technical decision-making [4,21]. Nevertheless, the literature highlights ongoing challenges, including limited availability of labeled data, variability in operating conditions, generalization across equipment types, model interpretability, and validation in real-world scenarios [10,19,22]. Overall, AI enhances not only predictive capabilities but also technical diagnosis and operational decision-making within engineering systems.

4. Deep Learning, Computer Vision, and Advanced Perception

Numerous engineering tasks require consistent and rapid interpretation of visual or spatial information. Applications such as industrial inspection, robotic perception, infrastructure monitoring, precision agriculture, autonomous navigation, smart manufacturing, and defect analysis depend on systems capable of processing images, videos, and complex scenes under varying operating conditions. Deep learning and computer vision technologies fulfill these requirements by enabling classification, object detection, semantic segmentation, pattern recognition, automated inspection, and scene analysis [7,8,16,23].

A significant advancement introduced by deep learning is the elimination of the need for manual definition of visual features. Deep learning models can autonomously learn relevant patterns from data, resulting in improved performance in automated perception tasks compared to traditional computer vision methods [7,16]. This advancement has facilitated the development of engineering applications that utilize visual information for inspection, monitoring, recognition, and operational response, in addition to observation [8,17,23,24]. Furthermore, real-time detection architectures, such as YOLO-based

models, have broadened the application of computer vision in scenarios that require both high accuracy and rapid response [25].

The deployment of these systems remains contingent upon practical factors that influence their reliability. Limitations such as data quality, dataset size, annotation consistency, lighting variation, environmental noise, computational cost, domain transfer, and implementation on embedded or edge devices persist as significant challenges [8,17,24].

5. Optimization, Control, and Autonomous Operation of Engineering Processes

Engineering systems are seldom assessed solely based on their predictive capabilities. In practical applications, prediction typically informs actions such as parameter adjustment, regulation of critical variables, resource allocation, energy reduction, or maintenance of safe and efficient operation. Consequently, AI has become increasingly significant in optimization, control, and intelligent process operation. Techniques including machine learning, reinforcement learning, system identification, and intelligent control are now employed to support decision-making in dynamic and uncertain environments [11,26–28].

This transformation is especially evident in industrial processes, energy systems, automation, transportation, and manufacturing. In these sectors, AI is increasingly integrated with real-time optimization and control strategies to enhance operational performance and facilitate adaptation to evolving conditions [26,27,29]. Rather than merely characterizing system behavior, these models inform the selection of operating policies, regulation of process variables, improvement of resource allocation, and support for adaptive responses during operation [11,30].

The practical implementation of these approaches remains contingent on challenges that cannot be addressed solely at the algorithmic level. Key issues include stability, operational safety, interpretability of learned policies, computational cost, transferability from simulation to real-world systems, and validation under diverse industrial conditions [26,28,29].

6. Cyber–Physical Integration, Digital Twins, and Intelligent Engineering Systems

The advancement of smart engineering systems relies on the integration of physical processes with digital environments. Digital twins and cyber–physical systems facilitate this integration by connecting sensors, operational data, computational models, AI algorithms, and feedback mechanisms within a unified engineering framework. This approach enables systems to progress beyond passive monitoring to include simulation, prediction, control, and adaptive decision-making [2,31–33].

In manufacturing, infrastructure, additive manufacturing, and distributed industrial environments, digital twins are used to represent real assets, track their behavior, detect anomalies, and support operational decisions [30,32,34,35]. When AI is incorporated into these architectures, the digital representation not only enables visualization of the system but also allows anticipation of failures, optimization of performance, adjustment of operating conditions, and support for predictive maintenance [31,35]. The connection with the internet of things, embedded systems, cloud computing, and edge computing also strengthens the possibility of working with information close to real-time operation [31,33].

The further development of these systems requires addressing challenges related to interoperability, data quality, synchronization between physical and digital layers, cybersecurity, latency, scalability, and validation under real operating conditions [32,34–36].

7. Energy, Sustainability, and Resource-Efficient Applications in Engineering

Energy-related engineering challenges represent a prominent domain in which AI is directly linked to sustainability objectives. The integration of renewable energy sources, variable demand management, power system optimization, and energy consumption reduction necessitates models that can address uncertainty, nonlinear dynamics, and substantial operational data volumes. Within this context, AI facilitates forecasting, control, fault detection, resource allocation, and energy management across smart grids, buildings, renewable generation systems, and industrial processes [5,37–39].

Smart grids exemplify this transition by integrating physical electrical infrastructure with communication systems, sensors, data analytics, and intelligent decision-making processes. Recent studies demonstrate that AI enhances grid stability, voltage regulation, renewable energy integration, demand-side management, asset monitoring, and operational resilience [5,37,40]. Comparable advancements are observed in building energy management and renewable energy systems, where learning-based models improve heating, ventilation, and air conditioning control, optimize wind power systems, forecast generation, and minimize energy waste [38,39,41].

The significance of this research area extends beyond efficiency improvements. AI also informs engineering decisions concerning sustainability, reliability, emission reduction, and the transition to cleaner energy systems [5,38,41]. However, successful implementation depends on data quality, cybersecurity, interoperability, explainability, regulatory compliance, and validation in real-world operating environments [37,40,42].

8. Implementation Challenges: Explainability, Robustness, Generalization, and Validation in Real-World Environments

The advancement of AI in engineering relies not only on the development of high-performing models. For these models to be effective in practical contexts, they must be integrated into decision-making workflows, function with imperfect data, maintain stability under changing working conditions, and generate explanations that can be assessed by human specialists. This requirement is particularly critical in applications where incorrect decisions may impact safety, operational continuity, product quality, energy consumption, or infrastructure reliability [13,43–45].

A primary challenge involves transitioning from models trained on controlled datasets to systems capable of functioning in diverse industrial environments. In such contexts, data may be incomplete, noisy, imbalanced, or insufficiently representative of all operating conditions [6,13]. Robustness encompasses more than maintaining model accuracy; it also requires that predictions and explanations remain dependable under distribution shifts, disturbances, uncertainty, or system degradation. Consequently, validation should address not only performance metrics but also stability, traceability, explanation quality, and relevance for technical decision-making [43,46].

Explainability has emerged as a fundamental requirement for the adoption of AI in engineering processes. In domains such as predictive maintenance, critical infrastructure, energy systems, computer vision, and process control, models must produce outputs that can be interpreted, audited, and connected to operational actions [44,45,47].

9. Future Perspectives for AI in Engineering Solutions

The forthcoming progress of AI in engineering will not rely exclusively on increasingly complex models or larger datasets. Instead, its successful integration will depend on transforming these models into reliable, interpretable, and practical tools for real-world systems. Achieving this objective requires the development of solutions capable of functioning under

physical constraints, variable conditions, incomplete data, safety requirements, and specific technical decision-making needs [6,48–50].

A significant future direction involves the development of hybrid models that integrate machine learning with physical knowledge, simulation, operational rules, and domain expertise. In engineering, this approach is particularly important because many systems cannot be treated as black boxes. Incorporating physical constraints, energy conservation, process dynamics, operating limits, and safety criteria into model design or validation is essential. This strategy can reduce reliance on extensive datasets, enhance generalization, and facilitate result interpretation [51,52].

It is also essential to reinforce the entire implementation cycle. AI should be integrated with sensors, embedded systems, edge computing, cloud platforms, digital twins, user interfaces, and human supervision mechanisms. Throughout this process, data quality, traceability, cybersecurity, interoperability, latency, and model maintenance are equally as important as predictive accuracy. The success of an AI-based engineering solution is determined not only by strong training performance but also by its sustained utility under real operating conditions [6,50,53].

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