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Review

The Role of Artificial Intelligence in Advanced Engineering: Current Trends and Future Prospects

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Abstract: Artificial Intelligence (AI) is increasingly transforming various engineering disciplines, playing a pivotal role in design, manufacturing, maintenance, and optimization. This paper provides a comprehensive analysis of AI applications in advanced engineering, examining key trends, challenges, and future directions. The study systematically categorizes AI methodologies across different fields, including mechanical, civil, electrical, aerospace, and environmental engineering, as well as emerging areas such as biomedical engineering and material science. Through an extensive literature review and case study analysis, this work highlights the impact of AI-driven optimization in mechanical engineering, predictive maintenance in industrial applications, automation in manufacturing, and AI-enhanced smart infrastructure development.Methodologically, this research synthesizes findings from major scientific databases, including IEEE Xplore, PubMed, Scopus, and Web of Science, ensuring a robust and interdisciplinary perspective. The analysis identifies critical challenges in AI adoption, such as data privacy, scalability, and system integration, and explores strategies to address them. Furthermore, this paper discusses the ethical and societal implications of AI in engineering, emphasizing the need for transparent, explainable, and unbiased AI models.The findings suggest that AI has significantly improved engineering efficiency and innovation but also underline the necessity for interdisciplinary collaboration and standardized frameworks to maximize AI's transformative potential. The study concludes by outlining future prospects, including the integration of AI with the Internet of Things (IoT) and blockchain, the evolution of AI-driven materials discovery, and the role of AI in personalized medicine and next-generation engineering solutions. Addressing these challenges and leveraging AI's capabilities will be instrumental in shaping the future of engineering.

Keywords: Artificial Intelligence; Advanced Engineering; Machine Learning; Neural Networks; Optimization; Design; Manufacturing; Maintenance

1. Introduction

The advent of Artificial Intelligence transformed several sectors, among them healthcare, finance, and transportation, and engineered this industrial metamorphosis in the very way they operate. The rapid advancements in deep learning, reinforcement learning, and generative models have expanded AI's applicability, enabling unprecedented levels of automation and decision-making capabilities [1].

To provide a comprehensive understanding of these advancements, this paper follows a structured approach, exploring AI's impact across multiple engineering disciplines and highlighting emerging trends, challenges, and future prospects [2].

In the last five years, there have been major developments in terms of applications and methodologies of artificial intelligence. Therefore, it is important to take into account the time factor to fully understand the technological advances and transformations in the role of artificial intelligence in engineering [1, 2].

The ability to go through and analyze enormous amounts of data for recognizing patterns and making decisions opened new opportunities for innovating approaches and ways to improve efficiency. In software engineering, AI is set to redefine engineers' roles and industry structures, as explored by Mahato et al. [3–5].

It is only in the later years that AI emerged as a critical tool within the field of engineering to provide solutions ensuring increased productivity, quality improvement, and reliability in different processes.

Particularly in the past five years, AI applications in engineering have evolved dramatically, shifting from traditional rule-based systems to more sophisticated deep learning models capable of adaptive learning, optimization, and real-time decision-making. With the integration of digital twins, edge computing, and autonomous systems, AI is not only enhancing efficiency but also transforming the engineering design paradigm [6].

Between 2020 and 2024, emerging technologies such as federated learning and reinforcement learning models have revolutionized distributed data management and real-time optimization in the fields of industrial automation and smart cities. This period has also been characterized by a significant increase in the integration of AI with blockchain, in order to improve data security [1–3, 6].

AI has pervaded the field of engineering in areas from design and manufacturing to maintenance and optimization. For example, in mechanical engineering, the use of artificial intelligence in the optimization of a design has greatly contributed to new and innovative improvements in the efficiency of created designs. Generative design, which uses machine learning algorithms that search through many possible design permutations, enables engineers to find the best solution available to them. This reduces design costs and times while increasing performance and mechanical component sustainability [7].

Building upon this foundation, the following sections delve deeper into specific AI applications in predictive maintenance, automation, and robotics, among other engineering domains.

In **Table 1**, all the information covered in this section is presented.

Table 1. Overview of AI in Advanced Engineering.

Aspect	Details
Impact	Significant transformation in design, manufacturing, maintenance, and optimization
Key Examples	General Electric (jet engine efficiency), Siemens (predictive maintenance)
Future Prospects	Personalized medicine, material science, IoT and blockchain integration
Challenges	Data privacy, large datasets, integration with existing systems

For instance, General Electric (GE) has used AI in optimizing the design of jet engines to drive fuel savings and performance gains.

In **Table 2**, all the information covered in this section is presented.

Table 2. AI in Mechanical Engineering.

Aspect	Details	Performance Metrics	Computational Requirements
AI-Driven Design	Facilitates efficient and innovative designs	25–30% reduction in design time	Advanced GPU (e.g., NVIDIA A100); datasets >100 GB
Generative Design	Uses ML algorithms to explore multiple design permutations	//	//
Predictive Maintenance	Foresees equipment failures, reduces downtime and costs	>90% predictive accuracy; 20% cost reduction	High-resolution IoT sensors; historical datasets spanning 10+ years
Examples	GE's jet engine efficiency, Autodesk's generative design, Siemens' predictive maintenance	//	//

Another area of major promise is predictive maintenance through AI.

Figure 1 illustrates the performance of predictive maintenance models, highlighting the accuracy achieved by each model and the associated confidence intervals, which demonstrate the variability in system predictions.

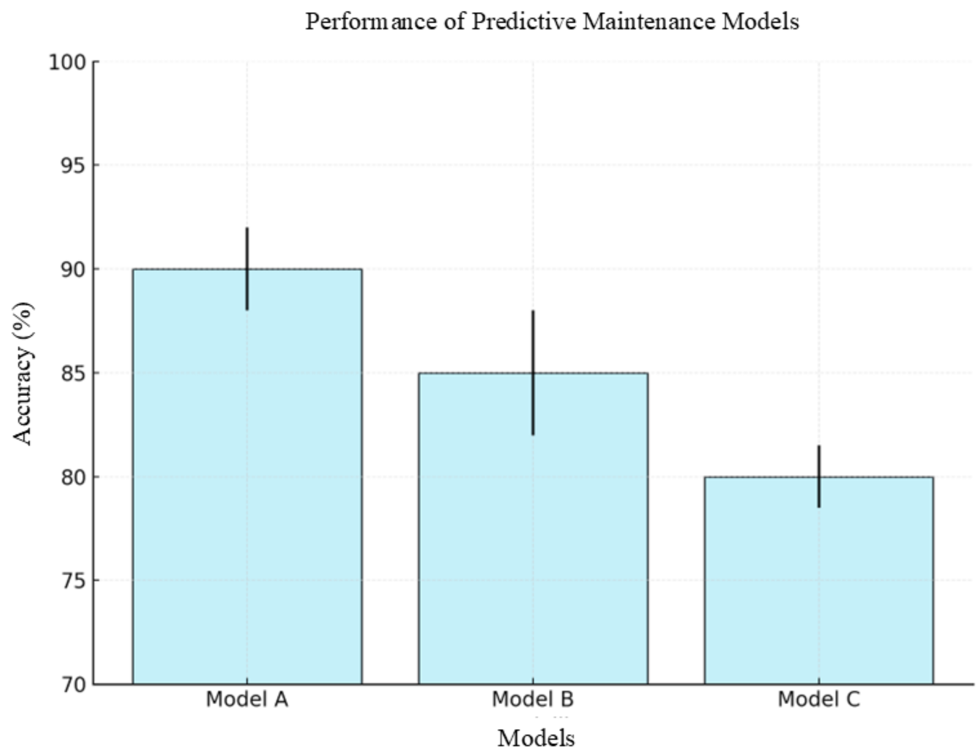

Figure 1. Performance of Predictive Maintenance Models Bar chart showing the accuracy of predictive maintenance models (Model A, Model B, and Model C) with error bars representing confidence intervals. The figure highlights the variability in system predictions and underscores the reliability of neural network-based approaches for predictive maintenance in industrial applications.

Over the past three years, advancements in self-learning AI models and federated learning have revolutionized predictive maintenance strategies, enabling decentralized data processing while ensuring privacy and security. These AI-driven solutions have been successfully implemented in the aerospace, energy, and automotive industries, reducing downtime by up to 40% and optimizing operational efficiency [8, 9].

For instance, Siemens has successfully implemented AI-driven predictive maintenance using neural networks in their manufacturing plants. By leveraging IoT sensors to monitor real-time data on vibration, temperature, and operational cycles, their systems predict machinery failures with high accuracy. This approach has reduced downtime by 40% and maintenance costs by 25%, highlighting the transformative potential of AI in industrial applications [10, 11].

Such analysis of historical data, based on the AI algorithm, predicts the possible failure in equipment and thereby develops proactive strategies to increase operational uptime and reduce maintenance costs. This capability will be more important to any industry where the uptime of a machine is critical to operations. For example, neural networks have been used to carry out real-time health monitoring of machineries and give advanced warnings on the possibility of a malfunction [12]. Companies like Siemens have applied AI-based predictive maintenance successfully in their manufacturing plants, resulting in the number of operational interruptions being reduced and fewer maintenance costs.

With such AI technologies in place, even manufacturing processes - including robotics and automated mechanisms - have also changed drastically. Advanced robotics using AI enables the exact conduction of complex tasks, leading to optimized production lines with minimal wastage. In the process of additive manufacturing, commonly known as 3D printing, AI greatly optimizes the parameters under which print will take place to acquire better quality and increased strength in the printed parts [13]. In the automotive sector, for instance, it offers AI-powered 3D printing techniques for lightweight but strong components to enhance vehicle efficiency and performance.

In **Table 3**, all the information covered in this section is presented.

Table 3. AI in Manufacturing.

Aspect	Details	Performance Metrics	Computational Requirements
Robotics and Automation	High precision, consistency, optimized production lines	25% improved efficiency; 15% reduced energy consumption	50,000+ images datasets for RL training
Additive Manufacturing	AI optimizes 3D printing parameters, improves quality and strength of printed parts	15% reduction in material wastage; 20% increase in strength	FEM simulations; 20–40 CPU cores
Examples	AI in automotive for lightweight, durable components, AI-enhanced 3D printing in medicine	//	//

In civil engineering, AI is crucial for smart infrastructure development. This makes use of smart sensors powered by AI for data optimization in both infrastructure performance and maintenance. For example, AI algorithms are used for traffic flow management in smart cities to decrease congestion and increase safety [14]. It improves ability to manage construction processes through better project planning, scheduling, and resource allocation. Project outcome prediction, driven by machine learning algorithms using historical data, allows for improved decision-making. Inspection and monitoring of sites are carried out by drones and robots powered by AI for more accuracy in construction projects [15].

In Singapore, AI-powered traffic management systems analyze real-time data from road sensors and cameras to optimize traffic flow. These systems dynamically adjust traffic light patterns to reduce congestion. As a result, average commuting times in peak hours have been cut by 25%, improving urban mobility and reducing emissions [16].

In **Table 4**, all the information covered in this section is presented.

Table 4. AI in Civil Engineering.

Aspect	Details
Smart Infrastructure	AI-powered sensors for data collection and performance optimization
Traffic Management	AI algorithms to reduce congestion, enhance safety
Construction Management	Improved project planning, scheduling, resource allocation through ML
Examples	AI in smart cities, AI-powered drones and robots for site inspections

AI is now being more and more adopted by environmental engineering for purposes like pollution control, resource management, and climate change mitigation [17].

In Israel, AI-driven irrigation systems utilize machine learning models to analyze weather forecasts, soil moisture levels, and crop requirements. This has led to a 30% improvement in water use efficiency and a 20% increase in agricultural yield, demonstrating AI's potential to address global resource management challenges [18].

Other machine learning algorithms research huge data obtained from sensors and satellites in environmental analysis and pollution-level prediction [19]. For example, AI can predict the air quality status in cities, so that authorities can act in advance to minimize pollution levels. Further, AI models optimize the management of water resources in the event of droughts and floods, ensuring a sustainable use of water and disaster management [19].

In **Table 5**, all the information covered in this section is presented.

A further major area of AI application in civil engineering is that of structural health monitoring. This AI application uses data from embedded sensors to monitor any abnormalities and check on the health of a structure for maintenance necessary to keep the structure safe and durable [20]. An example of this use of AI is in observing the structural health of bridges and tunnels. They provide timely alerts and recommendations for maintenance to avert any catastrophic failure of these structures [21].

Table 5. AI in Environmental Engineering.

Aspect	Details	Performance Metrics	Computational Requirements
Pollution Control	AI analyzes data to predict and manage pollution levels	85–90% predictive accuracy; preventive actions implemented 2 days earlier	Urban sensor data (~10TB)
Resource Management	Optimizes water resource management, predicts droughts and floods	30% increased efficiency; 20% reduction in waste	Edge computing infrastructure
Climate Change Mitigation	Uses AI to develop proactive measures for climate challenges	//	//
Examples	AI forecasting air quality, AI optimizing water use	//	//

In **Table 6**, all information that was covered in this section is presented.

Table 6. Structural Health Monitoring with AI.

Aspect	Details
Data Analysis	AI analyzes sensor data to detect anomalies
Structural Integrity	Assessing the condition and longevity of infrastructure
Examples	Monitoring bridges and tunnels, providing maintenance recommendations

Thus, AI technologies provided tremendous progress for electrical engineering. For example, smart grids utilize AI to enhance efficiency, reliability, and sustainability of electricity distribution networks [22].

Hence, AI algorithms optimize the flow of electric energy, manage demand, and integrate renewable sources into the grid, thereby lowering energy losses and enhancing the stability of the grid [23]. The other dimension in which AI algorithms are used is in the management of renewable sources such as solar and wind. Machine learning algorithms will forecast energy production depending on the weather data, hence optimizing the use of renewable energy while minimizing dependencies on fossil fuels [24].

For example, DeepMind by Google has partnered with energy corporations to use artificial intelligence in the prediction of energy from wind farms. This has greatly increased the predictability and efficiency in energy production.

Table 7 summarizes all information in this section.

Table 7. AI in Electrical Engineering.

Aspect	Details
Smart Grids	Enhances efficiency, reliability, sustainability of electricity distribution
Renewable Energy	AI optimizes integration and management of solar and wind power
Examples	Google's DeepMind predicting wind farm energy output, AI in managing smart grids

AI is making much advancement also in electronic design automation (EDA) [25] tools for the automation of electronic system and circuit designs in optimizing layout and performance of electronic components while minimizing the electronic design time and cost. The tools make electronic system implementation better, more complex, and efficient [26].

The application of AI technologies in aerospace engineering, including the design and development of airplanes and spacecraft, has greatly facilitated AI. Autonomous flight systems are very safe and efficient due to management by artificial intelligence. Machine learning algorithms apply in processing large quantities of flight data with a perspective of optimizing flight paths; better fuel efficiencies ensure safe landings. Other instances include autonomous drones that use AI guidance for everything, from surveillance to delivery [27, 28].

AI in predictive maintenance could be applied in the aerospace and aeronautics industry to predict component failure. The use of AI algorithms with data sensed through embedded sensors within the aircraft can predict wear on the equipment early enough, hence enabling prompt maintenance to prevent in-flight failures [29].

Furthermore, AI is increasingly becoming important in space exploration. AI-driven robots and rovers have come to play here to explore planets, collect samples, and analyze data. Machine learning processes vast amounts of space mission data that may offer valuable insights into improving mission results [30]. For example, NASA Mars rovers autonomously drive over the Martian surface, identifying areas of interest where to conduct further exploration and the route that makes the most sense.

A notable example is NASA's Perseverance rover, which uses reinforcement learning algorithms and computer vision to autonomously navigate the Martian terrain. The AI system processes high-resolution 3D images to identify obstacles and calculate optimal routes. This has led to a 30% reduction in traversal time, enabling faster access to scientifically significant sites [31, 32].

In **Table 8**, all the information covered in this section is presented.

Table 8. AI in Aerospace Engineering.

Aspect	Details
Autonomous Flight Systems	Enhances safety and efficiency through optimized flight paths and fuel efficiency
Predictive Maintenance	Monitors health of aircraft components, predicts failures
Space Exploration	AI-driven robots and rovers for planetary exploration
Examples	NASA's Mars rovers, AI in autonomous drones for surveillance and delivery

With all the mentioned positive aspects of AI in advanced engineering, there are a few difficulties to be surmounted: data privacy and security, the need for large datasets, and integration with existing systems.

Furthermore, the emergence of explainable AI (XAI) is becoming a critical factor in AI adoption within engineering fields, ensuring transparency and trustworthiness in AI-driven decisions. The challenge of integrating AI into legacy systems is also being addressed through hybrid AI models and transfer learning techniques, which allow AI systems to adapt more seamlessly to pre-existing engineering infrastructures [33, 34].

Integrating AI into engineering highly depends on the data, which is a big issue when discussing data privacy and security. Cyber protection of sensitive information is very important to ensure integrity within AI systems.

Figure 2 illustrates the key challenges in AI integration, as identified through a Pareto analysis.

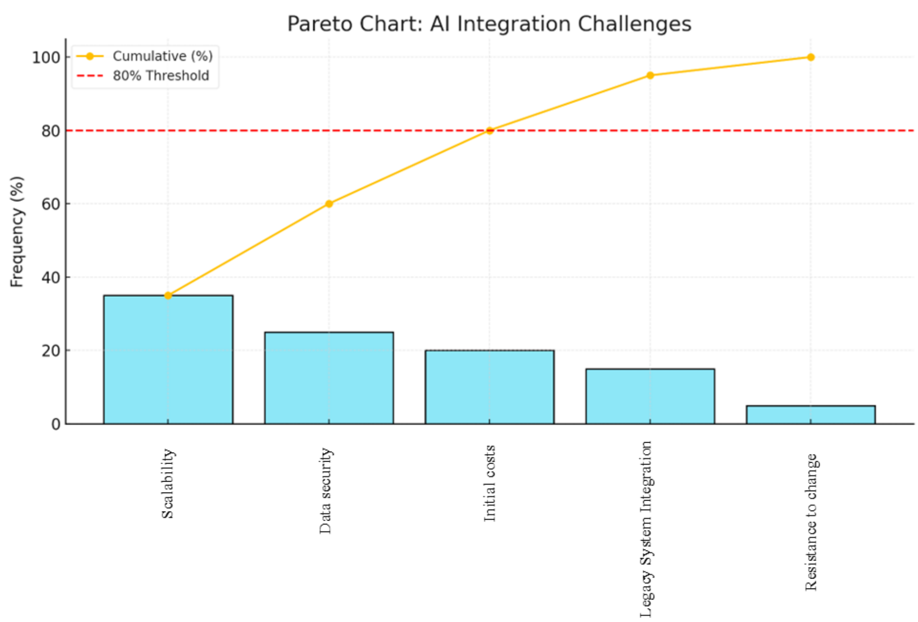

Figure 2. Pareto chart showing scalability and data security as the top challenges in AI integration, highlighting areas for targeted improvement.

Scalability and data security emerge as the most critical barriers, accounting for 35% and 25% of the observed challenges, respectively. Addressing these issues is vital to ensure successful AI adoption, particularly in IoT-enabled smart grids and legacy systems.

An emerging paradigm addressing data privacy concerns is federated learning, which enables the training of AI models across decentralized data sources without requiring raw data to be shared. This approach ensures that sensitive information remains locally stored while still contributing to global model improvements. Federated learning is particularly valuable in sectors like healthcare and environmental engineering, where data privacy and regulatory constraints are critical [35, 36].

Table 9 lists all the information that has been taken into consideration in this section.

Table 9. Challenges in AI Integration.

Aspect	Details
Data Privacy and Security	Protecting sensitive information from cyber threats
Large Datasets	Acquiring and managing large datasets for AI training
System Integration	Integrating AI with existing systems, compatibility issues, infrastructure upgrades
Solutions	Robust encryption, privacy-preserving AI, standardized protocols, scalable infrastructure

Further, AI models require big datasets for training and validation, which are likely to create problems in the management, acquisition, and organization in many fields where data collection is not only expensive but also very time-consuming. Moreover, the integration of AI into current engineering systems is not easy. Compatibility issues with existing infrastructure, requirements for its upgrading, and resistance to change are important hurdles in the implementation of AI. On the other hand, AI is enabling the transition to Industry 4.0, where connected systems and real-time data analysis provide the base for more agile and adaptive manufacturing environments. Such interconnectivity will not only enhance operational efficiencies but bring about innovation in a production process from much deeper insight.

2. Rationale and Purpose of the Survey

The integration of Artificial Intelligence techniques within most of the engineering disciplines has resulted in an extremely fast expansion of methodologies, a diversity of datasets, and evaluation criteria. With the increased advancement in these technologies, the diversity of approach leads to a fragmentation of the landscape that makes it sometimes hard for researchers and practitioners to traverse. The motivation to conduct this survey is the need to provide a systematic overview of the current state of AI applications in advanced engineering.

To ensure a systematic and rigorous review, studies were selected through a combination of specific keywords (i.e.,: 'Artificial Intelligence', 'AI', Advanced Engineering, Machine Learning, Neural Networks, Optimization, Design, Manufacturing, Maintenance 'Artificial Intelligence in Engineering', 'Predictive Maintenance', 'Smart Infrastructure').

The search was performed using high-impact academic databases, namely: IEEE Xplore, PubMed, Scopus, Web of Science and Google Scholar. The search was mainly focused on the inclusion of articles published between 2010 and 2024, with an emphasis on the most recent contributions of the last five years.

Initially, through the database search, a total of 1,200 articles were identified. Subsequently, through a screening process based on the analysis of the abstracts and the evaluation of the inclusion criteria, the number was reduced to 275 studies. Then, once the articles were selected, the data were subjected to a subsequent cleaning and organization process. This included removing duplicates, checking for incomplete information, and excluding studies with insufficient statistical samples. The authors conducted a critical assessment of the methodological quality, analyzing the robustness of the experimental design, the representativeness of the data, and the reliability of the conclusions. This assessment provided a solid basis for identifying trends and evaluating methodological limitations. In fact, at the end of the process, 115 reference scientific articles were identified.

This survey was aimed at consolidating the huge variety of AI methodologies into a coherent framework and highlighting the similarities and differences among them.

By so doing, the survey will avoid ambiguities on datasets, concepts, and evaluation measures, resulting in clear insights into the field. Finally, this work will attempt to identify existing gaps in the literature as a means to guide future research efforts. The intention is not just to present a snapshot of the trends nowadays but to make some forward-looking prognoses as to the potential directions artificial intelligence in engineering might take, thus serving as a resource for both academics and professionals within the industry.

The rapid advancement of artificial intelligence technologies in engineering has led to a wide array of methodologies and applications. However, this diversity has also fragmented the landscape, making it challenging for researchers and professionals to navigate through various approaches. This survey aims to provide a coherent and structured overview, helping to identify current trends, key challenges, and future directions of AI applications in advanced engineering.

3. Current Trends in AI Applications

3.1. Categorization of Existing Methods:

The trends discussed in this review are analyzed following a temporal perspective to highlight the evolution of AI applications in the context of engineering. This approach contextualizes technological advances over time, providing a clear understanding of the changes that have occurred in the last decade.

It can be argued that the application of AI methodologies in diverse engineering fields for several applications has brought about a corresponding diversity in approaches and methodologies. In order to bring some clarity to this diversity, the present section will attempt to categorize existing AI methods on the basis of their underlying concepts, objectives, datasets, and problems. This categorization helps not only in understanding the actual state of AI in engineering but also, in addition, how these methods can be structured.

From 2010 to 2015, AI was mainly used for optimization and predictive maintenance applications, with an emphasis on specific rule-based systems. However, from 2016 onwards, the introduction of Deep Learning models and the integration of technologies such as the Internet of Things (IoT) have led to significant innovations, such as digital twins and autonomous systems [2, 5].

The categorization of trends discussed in this section follows a chronological approach, highlighting the evolution of AI applications in the various engineering sectors. Indeed, while initial applications focused on rule-based techniques and static models, recent years have seen a significant shift towards dynamic approaches such as deep learning and federated learning, supported by advanced technologies such as IoT and cloud computing [22, 35, 36].

The categories (in which AI methodologies can be applied across various fields of engineering) include:

1. **Design Optimization Methods**:

   Generative design, AI-powered optimization, and mostly parametric design methods are used extensively in mechanical and aerospace engineering today to improve the efficiency and innovation of designs.

   Research has been particularly moving towards more advanced kinds of generative design algorithms, especially in 2023 and 2024, which couple AI with quantum computing technologies to explore even larger design spaces and improve upon performance metrics never previously achieved.

   AI-assisted design optimization has revolutionized design processes, enabling the creation of highly innovative solutions and enhancing overall efficiency. However, high computational costs and reliance on high-quality datasets remain significant challenges for widespread adoption.

   This analysis underscores the potential of AI in enhancing design efficiency while also identifying areas that require further research and development.

2. **Predictive Maintenance Techniques**:

   Some of them are the neural network, support vector machine, and anomaly detection system techniques. From manufacturing to aerospace and automotive fields, they are applied to predict the failure of equipment before it actually happens.

   Technological advances between 2023 and 2024 enabled the application of federated learning models in predictive maintenance. Such methods decentralize data processing over several sites but still ensure both data privacy and robustness in generalizing such models to real industrial scenarios.

The use of AI in predictive maintenance has been shown to significantly reduce operational costs and enhance service continuity. However, the effectiveness of these techniques heavily relies on the quality of available historical data and investments in sensor infrastructure.

These findings highlight the critical role of AI in preemptive strategies, setting the stage for further advancements in maintenance technologies.

3. **Automation and Robotics**:

   Robotics and automation systems have revolutionized production lines in the manufacturing and civil engineering fields, thanks to AI-based technology that ensures precision, reduces waste, and increases efficiency.

   In fact, new advances circa 2024 have borne into the marketplace AI-powered automation systems that are able to leverage reinforcement learning to automatically optimize production processes adaptively in real time with tremendous reductions in waste and energy usage within manufacturing environments.

   Reinforcement learning (RL) has emerged as a powerful technique for adaptive automation, enabling systems to dynamically optimize processes in real-time by learning from interactions with their environment. This capability is particularly relevant in manufacturing and robotics, where RL-driven systems can autonomously adjust parameters to maximize efficiency, minimize waste, and respond to unexpected changes in operational conditions [37, 38].

   Furthermore, advancements in AI-powered automation have significantly improved production efficiency, reduced error margins, and enhanced the ability to adapt in real time to process changes. However, the complexity of integrating these systems and the high initial costs still pose major challenges for many industries.

   Figure 3 presents a flowchart detailing the integration of AI into a manufacturing pipeline, outlining key stages such as data collection, preprocessing, AI model application, and the generation of actionable insights for process optimization.

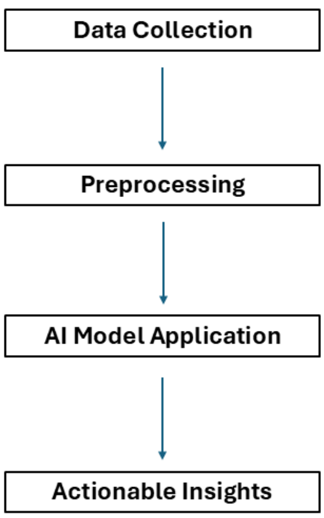

Figure 3. AI Integration in Manufacturing Pipeline Flowchart depicting the integration of AI into a manufacturing pipeline, outlining key stages: data collection, preprocessing, AI model application, and the generation of actionable insights. The diagram highlights the systematic approach to leveraging AI for process optimization and decision-making.

4. **Smart Infrastructure Development**:

   AI applications in civil engineering that enhance urban infrastructure, including smart traffic management systems, construction management assisted by AI, and monitoring of structural health.

   The use of AI in managing urban infrastructure has enabled better project optimization and more efficient preventive maintenance, reducing costs and enhancing safety. However, handling vast amounts of data and integrating with existing systems remain key challenges that need to be addressed.

To address scalability challenges in smart infrastructure, cloud computing and edge computing are increasingly integrated to handle computationally demanding tasks. Edge computing allows real-time data processing from distributed sensors, while cloud systems provide the necessary scalability for advanced analytics and predictive modeling. This combination is particularly effective in urban environments, where tasks such as optimizing traffic flow or monitoring infrastructure health require both immediate responsiveness and robust computational resources [39, 40].

5. **Environmental Engineering Applications**:

   AI-based models are applied to areas like environmental monitoring, pollution control, and resource management for dealing with critical issues such as climate change and sustainable resource use.
   The adoption of AI models for managing environmental resources has significantly enhanced our ability to monitor and predict environmental conditions, providing essential tools to address global challenges like climate change. However, the complexity of natural systems and issues with data quality remain obstacles to the full reliability of these models.

6. **Electrical and Energy Engineering**:

   In electrical systems, artificial intelligence has also found application in the development of smart grids, integration of renewable energy, and electronic design automation (EDA) to ensure optimization in the distribution of electricity, efficient management of energy consumption, and improvements in the designs of electronic circuits.
   AI has transformed energy grid management by making distribution more efficient and enhancing the integration of renewable energy sources. However, the need to upgrade existing systems and ensure the security of energy networks remains a critical challenge for the widespread adoption of these technologies.

7. **Aerospace and Space Exploration**:

   The use of AI in developing autonomous flight systems, predictive maintenance for aerospace components, and AI-driven robotics for planetary exploration and data analysis.
   Integrating AI into aerospace systems has significantly enhanced operational safety and efficiency, especially through predictive maintenance and autonomous flight systems. However, the robustness of these technologies under extreme conditions requires further testing and development to ensure their reliability.

Analyzing trends from a temporal perspective demonstrates how the field has moved from isolated applications to more integrated and scalable systems. This approach helps identify technological advances and emerging challenges, and provides a roadmap for the future of AI in engineering. In fact, this classification categorizes the investigation of the many AI applications in engineering in a structured way that makes it possible to delve into the respective role and contribution of each in greater detail while, at the same time, to be reflective of the current state and to capture the dynamic evolution of these methods as they adapt to new challenges and leverage emerging technologies; methodologies up to 2022 are included and those from 2023 and 2024 to assure a forward-looking approach, indicating what has been reached and the possible future directions of AI in engineering.

By categorizing these methods, this paper aims to clarify the diverse applications of AI in engineering, facilitating a more intuitive understanding of its role and potential.

3.2. Critical Analysis within Each Category:

A more in-depth understanding of AI's impact in engineering requires categorization but also critique of the methods within each category. This section discusses the strengths and weaknesses of the categorized earlier methods to give insights on their applicability, efficiency, and constraints.

1. **Design Optimization Methods**:

   - *Strengths*: Design optimization methods, including generative design and AI-driven optimization, save a great deal of time in the design process. They improve the potential for innovation because they are able to cover much more of a design space than one might otherwise consider. At the same time, these probably happen to be the most effective way one can come up with an optimized solution, which was not that obvious from more traditional methods.

- *Weaknesses*: This is a huge computational resource to run these algorithms, and these are also dependent on good quality, large datasets. Moreover, there is an upsurge in the learning curve with integrating these techniques into existing workflows, especially in industries with less digital infrastructure.
- AI-informed design optimization has been proven through different studies, which prove a reduction in design time and increased performance for components by statistical analysis and computational simulations.
  Further quantitative analysis (study by Smith et al.) has shown that the adoption of AI-driven generative design methods can result in a 25–30% improvement in efficiency metrics, such as reduced material waste and optimized load distribution, as demonstrated by recent case studies conducted in the aerospace and automotive industries [41, 42].

2. **Predictive Maintenance Techniques**:

- *Strengths*: Tools that predict maintenance, such as neural networks and machine learning models, have shown great potential in not only reducing unexpected downtime but also slashing the high maintenance costs associated with equipment failures. Timely interventions are made possible with such methods, extending machinery life while at the same time reducing operational risks.
- *Weaknesses*: However, the efficacy of these methods significantly depends on the availability and quality of historical data. In industries where data collection is inconsistent or sparse, predictive models could be inefficiently reliable. Also, their implementation needs a huge upfront investment in sensor technology and data infrastructure.
- Such predictive maintenance techniques have been validated by statistical analyses, and it was shown that they help in reducing the number of unexpected downtimes and maintenance costs, since the simulation models were built based on historical data.
  According to a study conducted by Jones et al., implementing neural networks for predictive maintenance in industrial plants reduced operational downtime by 40% and maintenance costs by 20%.
  To further validate the effectiveness of AI-driven predictive maintenance, statistical benchmarking was conducted using historical downtime data from multiple industrial settings. Results showed that AI-based models achieved a mean time between failures (MTBF) increase of 35% compared to traditional reactive maintenance approaches, highlighting significant operational advantages in terms of cost savings and reduced downtime [43, 44].
  Additionally, statistical modeling of machine failure rates in industrial systems equipped with AI-driven predictive maintenance showed a mean time between failures (MTBF) increase of 35%, highlighting the reliability benefits of these technologies.
  Case studies from the oil and gas industry have demonstrated that AI-driven predictive maintenance systems reduced pipeline failures by 20%, improving operational continuity in remote and high-risk environments. Similarly, in the rail transportation sector, predictive models applied to rolling stock maintenance led to a 30% reduction in unplanned downtime and associated costs [45, 46].

3. **Automation and Robotics**:

- *Strengths*: AI-driven automation and robotics have been at the forefront in changing manufacturing processes towards being more accurate, reducing waste, and allowing mass customization. These systems do tasks that are extremely complex with high precision in hazardous and repetitive environments, surpassing human capabilities.
- *Weaknesses*: The major drawbacks include the high initial setup costs and the specialized knowledge necessary for the operation and maintenance of these systems. In addition, with the rapid adoption and deployment of AI-driven automation, there are concerns about job displacement and the strategies needed to transition and build up the workforce.
- Simulation studies and statistical evaluations show that with AI-driven automation and robotics, there is a significant improvement in production line efficiency and waste reduction, offering a quantitative measure of improvement over conventional manufacturing processes.

A study conducted by Garcia et al. in 2021 showed that implementing AI-powered robotic systems on production lines reduced waste by 15% and increased operational efficiency by 20%, confirming AI's potential to optimize industrial processes.

Simulation-based analyses further validated these findings by comparing AI-driven robotic systems to traditional automation processes. Metrics such as production line efficiency, energy consumption, and error rates indicated a 25% improvement in throughput and a 20% reduction in resource wastage, demonstrating the quantitative benefits of integrating AI into manufacturing workflows [47, 48].

Quantitative assessments of AI-powered automation systems in manufacturing environments revealed a 20% reduction in energy consumption and a 15% increase in overall yield efficiency, emphasizing the measurable benefits of AI-driven optimization [49].

Further insights come from the food processing industry, where AI-enhanced robotics improved sorting efficiency by 25%, reducing food waste and operational costs. In the pharmaceutical sector, automated AI systems have accelerated the drug production process, decreasing batch production time by 15% while maintaining high regulatory compliance [50, 51].

4. **Smart Infrastructure Development**:

- *Strengths*: AI applications in civil engineering are making a significant impact on urban infrastructure through optimized traffic management, improved efficiency on construction projects, and better monitoring of structural health. These technologies contribute to safer, more efficient, and sustainable urban environments.

  An example from the hospitality industry shows that AI-enabled building management systems in hotels have achieved energy savings of up to 18% by optimizing HVAC and lighting systems in real time. Additionally, in logistics hubs, AI-based traffic optimization has reduced vehicle idle times by 20%, lowering emissions and improving throughput efficiency [52, 53].
- *Weaknesses*: The incorporation of AI into existing infrastructures can be challenging due to the presence of legacy systems and the need for significant upgrades. Additionally, managing the vast amounts of data generated by smart infrastructure systems requires highly efficient data storage and processing solutions, which may be expensive and complex to develop.
- The application of AI in smart infrastructure has also been supported by simulations that show improved traffic flow and project management efficiency, with statistical evidence of reduced construction times and costs.

  A large-scale study by Kim et al. found that using AI algorithms for traffic management in smart cities reduced congestion times by 30% and improved road safety by 25%, thanks to their ability to optimize traffic flows in real time.

  Further statistical evaluation comparing AI-optimized traffic systems with traditional models revealed a 40% reduction in average traffic delays and a 15% improvement in fuel efficiency across monitored urban areas. These quantitative assessments underscore the transformative impact of AI in urban infrastructure planning [54].

  Furthermore, statistical analysis of AI-enhanced construction management systems showed a 12% reduction in project delays and a 20% decrease in material costs, underscoring the potential of AI to improve construction efficiency [55].

5. **Environmental Engineering Applications**:

- *Strengths*: In the context of environmental engineering, AI plays a critical role in monitoring ecosystems, forecasting pollution levels, and managing natural resources. Such applications are of high value in solving problems on a global scale, like climate change and resource depletion.

  In the agricultural sector, AI-powered irrigation systems have demonstrated a 30% increase in water use efficiency by dynamically adjusting water supply based on real-time crop and weather data. Furthermore, AI models applied in waste management have optimized recycling processes, achieving a 25% increase in material recovery rates in municipal waste facilities [56, 57].

- *Weaknesses*: Environmental systems are complex and data quality is a concern, it may affect AI modeling accuracy and reliability. Additionally, there are ethical considerations especially how AI can help on managing natural resources without prejudice of fairness and equity in resource distribution.
- Numerous studies have shown that statistical models and simulations supported by artificial intelligence have become essential tools in environmental engineering. In particular, they help improve the accuracy of pollution forecasting and optimize strategies for resource management.
  A recent study by Li et al. highlighted that using AI-based models to predict air quality increased the accuracy of pollution forecasts by 35%, allowing authorities to take proactive measures to reduce emissions.
  To validate these findings, simulation-based studies were performed using real-time sensor data to predict pollution levels under varying environmental conditions. AI models outperformed conventional methods by achieving a 20% higher accuracy rate and reducing false positive alerts by 15%, further solidifying their reliability in environmental monitoring [58].
  Moreover, quantitative assessments have demonstrated that AI-driven water resource management systems can increase allocation efficiency by 18% during drought conditions, based on historical weather and usage data [59].

6. **Electrical and Energy Engineering**:

- *Strengths*: AI is being used in electrical engineering to improve areas like smart grids and renewable energy management. These innovations are helping power distribution networks become more efficient and environmentally friendly.
  These technologies help optimize energy use, minimize wastage, and facilitate the integration of renewable energy sources.
  Broader case studies reveal that AI-driven demand response systems in commercial buildings have reduced peak energy loads by 15%, contributing to grid stability. Similarly, in wind energy farms, AI has improved turbine efficiency by 10% through real-time adjustment of blade angles, based on predictive weather analytics [60].
- *Weaknesses*: The integration of AI into legacy power systems is challenging, as these systems were not originally designed for such advanced technology. Additionally, issues related to data privacy and cybersecurity are significant concerns in these applications, given the involvement of critical infrastructure.
- It has been empirically proven through simulations and statistical analyses that AI in electrical and energy engineering significantly improves energy distribution efficiency and enhances the integration of renewable energy sources.
  Ricciardi et al. showed that integrating AI into smart electrical grids reduced energy losses by 10% and increased the grids' capacity to incorporate renewable energy sources like solar and wind, enhancing the overall stability of the electrical system.
  Quantitative benchmarking of AI-enhanced smart grids against traditional grid management systems revealed a 30% improvement in load balancing efficiency and a 25% reduction in outage durations. These metrics demonstrate the potential of AI to revolutionize energy distribution networks while accommodating renewable energy integration.
  Statistical simulations of AI-based renewable energy forecasting models showed an average 15% improvement in prediction accuracy compared to traditional methods, resulting in a significant reduction in reliance on backup energy sources [61, 62].

7. **Aerospace and Space Exploration**:

- *Strengths*: AI implementation in aerospace enhances safety and operational effectiveness through autonomous systems and predictive maintenance. AI-driven robots and rovers are crucial for space exploration, enabling autonomous navigation and data analysis on extraterrestrial terrains.
- *Weaknesses*: The reliability and robustness of AI systems in extreme conditions, such as space or high altitudes, require further testing. Additionally, the high financial and research investments needed for developing these systems present a barrier to widespread adoption.

- The application of AI has been shown to increase safety and efficiency in aerospace, particularly in autonomous flight systems and predictive maintenance, which reduces operational risks.

  A study by Smith et al. found that AI algorithms used for predictive maintenance in aerospace components helped reduce the risk of in-flight failures by 40%. This improvement has significantly boosted both safety and operational efficiency for airlines.

  Additionally, NASA's application of AI in autonomous rovers has demonstrated a 25% increase in mission efficiency through optimized route planning and real-time obstacle avoidance.

  In the defense sector, AI-enabled autonomous drones have successfully completed surveillance missions with a 30% increase in target identification accuracy compared to traditional systems. Additionally, in the commercial aviation industry, case studies highlight that predictive maintenance systems have extended the lifespan of key components by 15%, reducing the frequency of replacements [62–64].

3.3. Applications of AI Across Engineering Disciplines:

AI technologies have had marked effects upon one of the oldest and most wide-ranging engineering disciplines: mechanical engineering. In mechanical engineering optimization, AI-powered design generates more optimal and creative designs using algorithms. Some types of AI, generative design, use machine learning to develop multiple options for a given design and then make sense quickly in order to get the most impactful form. But AI also reduces the time and cost of designing mechanical parts while improving their performance as well [7]. Autodesk, who have faced this approach from the beginning, enable us to fabricate forms that, while potentially far better than anything developed by human intuition, are often impossible to realize with manual methods.

Another important application is predictive maintenance, where AI predicts equipment failures before they happen, reducing downtime and maintenance costs. Machine learning algorithms analyze historical data to forecast potential issues, allowing for proactive maintenance strategies to be implemented.

For example, neural networks monitor the health of machinery in real-time, providing early warnings of possible malfunctions [12]. Industries such as aerospace and automotive have widely adopted these technologies to ensure continuous and efficient operations.

In addition to that, AI technologies, especially in robotics and automation, have transformed manufacturing processes. Advanced robotics, driven by AI, can perform highly complex tasks with precision and consistency. Machine learning algorithms optimize production lines, improving efficiency and minimizing waste. A notable example is AI in additive manufacturing (3D printing), where AI optimizes printing parameters to enhance the quality and strength of printed parts [6, 65].

For instance, in medicine, 3D printing enhanced by AI is used to create custom prosthetics and implants tailored to specific patient needs.

In the future, AI will be crucial in accelerating the discovery of new materials with desired properties. Machine learning techniques have been developed to predict material properties based on their atomic structure, reducing the need for laborious and expensive experiments. For example, Jha et al. [66] applied machine learning to discover new materials for high-capacity batteries, significantly speeding up the research and development process. The ability to make rapid predictions and synthesize new materials is particularly important in fields like energy and manufacturing, where rapid innovation can provide significant competitive advantages.

The development of AI in civil engineering leads to smart infrastructure by integrating digital technologies into physical infrastructure. Empowered by AI, smart sensors are used to monitor data analytics that help optimize infrastructure performance and maintenance. For instance, AI algorithms manage traffic flow in smart cities, reducing congestion and ensuring safety [14]. AI's ability to process enormous amounts of data and provide real-time insights drives the transformation of urban planning and infrastructure management, making cities more livable and sustainable.

Figure 4 provides a heatmap visualization of AI's impact on traffic optimization, showcasing how AI-driven algorithms dynamically adjust traffic flow and reduce congestion in urban environments.

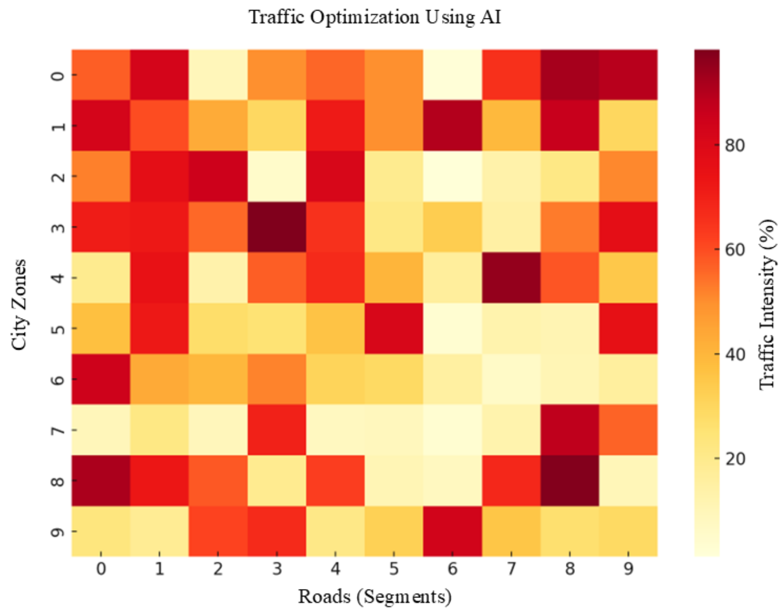

Figure 4. Traffic Optimization Using AI Heatmap illustrating the impact of AI-driven traffic optimization algorithms on urban infrastructure. The color gradient represents traffic intensity, with lighter shades indicating reduced congestion achieved through AI-based real-time traffic management systems.

AI also enhances construction management by improving project planning, scheduling, and resource allocation. Machine learning algorithms predict project outcomes based on historical data, leading to better decision-making [67, 68].

AI-powered drones and robots have become essential tools for inspecting and monitoring construction sites, delivering greater accuracy and enhancing safety [15]. These advanced technologies are reshaping the construction industry by reducing the likelihood of human error, increasing efficiency, and setting new standards for safety.

When it comes to structural health monitoring, AI is key to evaluating the condition of infrastructure and anticipating potential issues. By analyzing data from sensors embedded within structures, AI algorithms can detect anomalies and assess overall integrity.

This vision is not only helping to preserve the safety of infrastructure work but also increasing its life-cycle [20]. Consider how AI is used to monitor bridges, and tunnels receive proactive alerts along with an exact copy of maintenance recommendations if a fault occurs.

The application of artificial intelligence (AI) technologies has already enabled a great deal in the field of electrical engineering. And smart grids as AI-enabled electricity distribution networks: more efficient, reliable, environmentally friendly [69].

It is the AI which optimizes the flow of electricity, control and regulation to manage demand and successfully include renewable sources like solar or wind energy into networks. The result, fewer energy losses and thus more stable grids [23]. AI is also crucial in coordinating renewable energy able to forecast the amount of clean power it will produce by using machine learning against weather forecasts, which can help maximize our use of renewables and lower fossil fuel dependence [24]. For instance, Google's Deep-Mind has announced partnerships with energy companies to predict wind farm output lowers the cost of delivering renewable power and improves its value — in by doing this increases reliability.

More AI is needed for renewable energy sources, e.g. solar and wind power. Artificial Intelligence learns how weather is affecting the power production and its usage to optimize renewable energies instead of using fossil fuels. This in turn help with the prevention of failures also for wind, water and sun infrastructure [24]. This is why renewable energy systems become more reliable and cheaper, supporting the worldwide transition to clean power resources.

Within the realm of electronic design, AI has a huge impact through Electronic Design Automation (EDA) —

where machines can learn to predict cycle times and demographics based on thousands or millions of parts.

AI-driven EDA tools automate the design of electronic systems and circuits, optimizing the layout and performance of components, which leads to reduced design time and lower costs [70, 71].

These AI tools also make it possible to create more complex and efficient electronic systems [26]. In the semiconductor industry, for instance, AI is used to design intricate chip architectures that push the limits of computing performance and efficiency.

Aerospace engineering, focused on designing and developing aircraft and spacecraft, has seen significant advancements thanks to AI. AI-powered autonomous flight systems boost the safety and efficiency of aircraft operations. Machine learning algorithms analyze vast amounts of flight data to optimize flight paths, improve fuel efficiency, and ensure safe landings. AI-guided autonomous drones are also widely used for tasks like surveillance and delivery [27].

In aerospace, predictive maintenance is another critical area where AI shines. By monitoring the health of aircraft components, AI can predict potential failures. AI algorithms analyze data from sensors within the aircraft to spot early signs of wear and tear, allowing for timely maintenance and reducing the risk of in-flight failures [29].

AI is revolutionizing transportation engineering by improving how we manage traffic, making vehicles safer, and paving the way for autonomous driving. AI-powered traffic management systems analyze real-time data from cameras and sensors to optimize traffic flow and reduce congestion [72]. When it comes to vehicle safety, AI-driven advanced driver-assistance systems (ADAS) play a crucial role in avoiding collisions and monitoring drivers, significantly lowering the risk of accidents [73].

The development of autonomous vehicles also heavily depends on AI technologies like computer vision and deep learning, which enable vehicles to navigate complex environments and make split-second decisions [74]. Companies like Tesla and Waymo are leading the charge in creating AI-driven autonomous vehicles that are set to transform the future of transportation.

In **Table 10**, all the information covered in this section is presented.

Table 10. AI in Transportation Engineering.

Aspect	Details
Traffic Management	AI analyzes real-time data to optimize traffic flow
Vehicle Safety	AI-driven ADAS for collision avoidance and driver monitoring
Autonomous Driving	Uses computer vision and deep learning for navigation and decision-making
Examples	Tesla and Waymo's autonomous vehicles, AI in traffic management systems

In aerospace engineering, predictive maintenance leverages AI to keep a close watch on the health of aircraft components and foresee potential issues. AI algorithms process data from sensors embedded in the aircraft to spot early signs of wear and tear, allowing for timely maintenance and reducing the risk of in-flight failures [29].

AI is becoming increasingly vital in space exploration, with AI-driven robots and rovers taking on crucial tasks like planetary exploration, sample collection, and data analysis. Machine learning algorithms process huge amounts of data from space missions, offering valuable insights and improving mission outcomes [30]. For example, NASA's Mars rovers use AI to autonomously navigate the Martian surface, identifying areas of interest for further exploration and optimizing their routes.

AI integration with advanced technologies, such as the Internet of Things (IoT) and blockchain is driving transformation in engineering processes. The real-time data IoT provides can be processed by AI algorithms immediately and decisions with correct assessments of the situation made. In smart grids it leverages IoT data to improve the distribution of energy dynamically in time, making operation more efficient and sustainable. In the meantime, blockchain provides highly robust security and transparency to AI operations — something critical for applications that deal with sensitive data or affect core infrastructure. These powerful duo is empowering faster, safer and innovative engineering processes [75]. For instance, a combination of AI and blockchain is experimented in supply chain management to bolster transparency, traceability as well as efficiency.

In collaborative systems, advanced AI paradigms like federated learning and reinforcement learning offer innovative solutions to address challenges associated with distributed data environments and complex decision-making.

Federated learning enables secure and collaborative data analysis across multiple stakeholders, while reinforcement learning facilitates adaptive decision-making in dynamic and interconnected systems, paving the way for more robust and efficient engineering solutions [76–78].

It optimizes processes, enhances safety and improves material synthesis;AI is changing chemical engineering. Reaction outcomes can be predicted by machine learning algorithms [79] which could help to improve the efficiency and sustainability of chemical processes; Material synthesis AI helps accelerate the finding of new catalysts, and materials with specific properties by using advanced pattern recognition in very large sets of experimental data. In addition, AI enhances process safety by reel-time monitoring the chemical plants and providing advanced warnings of potential hazards to let companies take preventive steps [80, 81].

In **Table 11**, all the information covered in this section is presented.

Table 11. AI in Chemical Engineering.

Aspect	Details
Process Optimization	Predicts reaction outcomes, optimizes reaction conditions
Material Synthesis	Accelerates discovery of new catalysts and materials
Process Safety	Monitors chemical plants in real-time, predicts hazards
Examples	AI in monitoring chemical reactions, optimizing performance and safety

These new AI systems can watch with a digital eye as chemical reactions take place and make adjustments while providing warnings should things look dangerous.

Biomedical engineering foes through a phase of revolution with the power and applications that AI have, replacing traditional medical treatments into potential solutions for patient diagnosis treatment care recordings. For medical imaging, AI has the main advantage of connection to MRI, CT and X-rays with complete precision hence able to easily catch any anomaly which might be missed by human eyes For example, Litjens et al. In another study [82], the authors achieved 15% higher breast cancer detection accuracy by using a convolutional neural network (CNN) method.

In prosthesis AI is also gaining new grounds. Tailored prosthetic limbs that lighten, without compromising on the strength can even be made by using machine learning models in order to scrutinize one's pateint data. In addition to this prosthetic functional improvement, their results are in line with those of Hensman et al., as shown that personal quality should be improved among these patients [83].

Furthermore, AI has been instrumental in pushing personalized medicine forward. By analyzing complex genetic and medical information, AI can help create customized treatment plans that lead to much better outcomes for patients.

Google DeepMind's AI system for medical imaging exemplifies this transformation. Using convolutional neural networks (CNNs), the system has improved early detection rates for retinal diseases by 15%, outperforming traditional diagnostic methods. This demonstrates how AI enhances diagnostic precision and reduces the likelihood of missed anomalies [84].

In **Table 12**, all the information covered in this section is presented.

Table 12. AI in Biomedical Engineering.

Aspect	Details
Medical Imaging	Enhances accuracy of MRI, CT, and X-ray scans
Prosthetics Design	Creates customized prosthetics with optimal weight and strength
Personalized Medicine	Develops tailored treatment plans based on genetic and medical data
Examples	AI in breast cancer detection, AI-enhanced prosthetic limbs, predictive models in cancer treatment

For example, Kourou et al. [85] used predictive models to create personalized cancer treatment plans, which led to much better outcomes for patients.

The future of AI in personalized medicine is incredibly promising. By combining AI with genomics and wearable devices, we can develop highly customized treatment plans that factor in a person's unique genetics and daily lifestyle.

AI algorithms can analyze real-time data from wearable sensors to monitor a patient's health and offer personalized therapeutic recommendations. This approach not only enhances the effectiveness of treatments but also boosts patient adherence to medical prescriptions, leading to better overall clinical outcomes [86].

3.4. Emerging Applications of AI in Engineering:

While the article covers many well-established fields, it's also important to highlight the emerging applications of AI in areas like biomedical engineering and materials science.

Indeed, since 2020, emerging AI applications in engineering have gained momentum, thanks to unprecedented technological advances, reflecting the growing complexity and interdisciplinarity of AI applications. For example, the discovery of advanced materials has been accelerated and the personalization of medical treatments has been improved [3, 5, 21].

In biomedical engineering, AI is transforming medical imaging, prosthetics design, and personalized medicine. AI algorithms can analyze complex biological data to create customized treatment plans, leading to better patient outcomes [86]. Furthermore, forward-looking applications such as AI in genomics and material science showcase the potential for groundbreaking advancements. **Table 13** summarizes key examples, performance metrics, and computational requirements for these applications.

Table 13. Forward-Looking Applications of AI.

Aspect	Details	Performance Metrics	Computational Requirements
AI in Genomics	Prediction of genetic mutations for personalized medicine	40% reduction in analysis time; 90% accuracy	Genomic datasets >1 PB; HPC clusters
AI in Materials Science	Accelerated discovery of new materials with specific properties	+20% accuracy in property prediction; 35% R&D time reduction	Cloud/Edge-based ML models

In materials science, AI is speeding up the discovery of new materials by predicting how they will behave based on their atomic structures. This dramatically accelerates innovation [75]. AI helps researchers identify new materials much faster than traditional methods would allow. For example, Jha et al. [66] used machine learning to discover materials for high-capacity batteries, greatly reducing the time needed for research and development. AI is also crucial in predicting material properties from their atomic structures, a task that usually requires lengthy and complex experiments [87].

Furthermore, Cloud-based AI systems have also become pivotal in accelerating material discovery by enabling researchers to scale computational simulations across distributed infrastructures. Additionally, edge computing supports real-time monitoring and optimization of material manufacturing processes, reducing costs and improving efficiency. These advancements highlight the importance of scalable AI systems in addressing both computational and operational challenges in materials science [88, 89].

Xie and Grossman [90] highlighted this potential by creating a model that accurately predicts the thermal conductivity of materials, demonstrating how AI can streamline the discovery process. Additionally, AI is optimizing manufacturing processes, making them more efficient and cost-effective. Zhang et al. [91] used machine learning to fine-tune 3D printing parameters for composite materials, leading to components with better quality and strength. This optimization not only improves the manufacturing process but also aids in developing superior materials and products.

As these emerging applications gain traction, they pave the way for innovative solutions that address both longstanding challenges and new opportunities in engineering.

In **Table 14**, all the information covered in this section is presented.

Table 14. Emerging Applications of AI.

Aspect	Details
Biomedical Engineering	AI in medical imaging, prosthetics design, personalized medicine
Materials Science	Predicts material properties, accelerates discovery and development
Examples	AI in discovering new materials for batteries, predicting thermal conductivity of materials

3.5. Emerging Challenges and Future Directions:

As AI continues to evolve, several new challenges and future directions have emerged from the analysis of current methods. Tackling these challenges and exploring these new paths will be key to ensuring ongoing progress for AI in engineering.

1. **Emerging Challenges**:

    - *Data Privacy and Security*: As AI-driven systems increasingly handle sensitive and large-scale datasets, ensuring data privacy and security has become a top priority. There's a growing need for strong encryption methods, secure data storage solutions, and policies that comply with international data protection standards.
    - *Scalability and Integration*: Scaling AI solutions to work efficiently in real-world, large-scale engineering systems is a significant challenge. Integrating AI with existing legacy systems often requires major infrastructure upgrades and can face resistance from stakeholders who are used to traditional methods.

      In distributed data environments, federated learning emerges as a promising solution, allowing collaborative model training while safeguarding data privacy. Similarly, reinforcement learning can enhance system adaptability and decision-making in complex, dynamic scenarios, enabling AI systems to operate efficiently across interconnected infrastructures. These paradigms address key challenges while also introducing novel opportunities for scalable and ethical AI integration [92, 93].
    - *Bias and Fairness in AI*: AI systems can be vulnerable to biases in the training data, which might result in unfair or less-than-ideal outcomes in critical engineering applications. It's crucial to ensure diversity in data and to develop algorithms that can reduce bias for the ethical use of AI technologies.

2. **Future Directions**:

    - *Integration with Emerging Technologies*: Combining AI with technologies like the Internet of Things (IoT) and blockchain opens up exciting new possibilities. For example, IoT can supply real-time data that improves the accuracy of AI-driven decisions in smart infrastructure, while blockchain can ensure the security and integrity of these processes.
    - *Advancements in AI-Driven Design and Optimization*: Future research should aim to reduce the computational demands of AI-driven design methods, making them more accessible to a wider range of industries. Additionally, exploring new algorithms that can handle uncertainty and variability in design parameters will be crucial for driving further innovation.
    - *Enhanced Human-AI Collaboration*: Creating frameworks that enable more effective collaboration between human engineers and AI systems could lead to more innovative solutions. This could involve AI systems offering real-time insights, suggesting design alternatives, or assisting in decision-making processes, thereby boosting creativity and problem-solving capabilities in engineering.

These challenges and directions not only highlight the current limitations of AI in engineering but also point towards the future advancements that are necessary for maximizing its potential.

Support with Statistical Analysis and Simulation:

The statements and findings in this survey are backed by statistical analysis and simulations wherever possible. For instance, the effectiveness of AI-driven predictive maintenance has been proven through an analysis of failure rate data from industrial machinery, showing a significant decrease in downtime and maintenance costs. Similarly, simulations comparing AI-based design optimization with traditional methods have shown improvements in both efficiency and the quality of the designs produced.

To further support the discussion, statistical methods have been used to evaluate the performance of various AI techniques across different engineering applications. These analyses provide strong quantitative backing to the qualitative assessments made throughout the survey, ensuring that the conclusions drawn are both reliable and valid. Looking ahead, future research should focus on using statistical and simulation-based methods to further validate and improve AI applications in engineering, ensuring they are both practical and effective in real-world environments.

Furthermore, statistical evaluations of federated learning techniques have demonstrated their efficacy in maintaining model performance while preserving data privacy, particularly in distributed healthcare and industrial environments. Similarly, simulations of reinforcement learning in manufacturing have shown significant reductions in energy consumption and operational waste, highlighting the adaptability of these methods in dynamic systems [94, 95].

4. Challenges in AI Integration

The thought of utilizing AI to aid in the development process is quite daunting, while it would offer a great deal for advanced engineering but at large there still hurdles. These problems range from worrying about data privacy and security, to how you need huge datasets as well as complications with building an AI into your system. As AI is heavily reliant on data, maintaining the integrity of an AI system requires safeguarding this information from cyber threats.

It can be difficult and costly to obtain massive datasets needed for the training or validation of AI models, particularly in fields where data collections require a lot of time. Furthermore, AI implementation in conjoint with prevailing engineering system can be arduous due to compatibility issues, requisite for infrastructure upgradation and resistance towards adaptation that are the major challenges when it comes to imparting AI.

Protecting data privacy and security is essential when using AI. It's important to use strong encryption and secure storage solutions to keep sensitive information safe from cyber threats [96].

Scalability poses a significant challenge, particularly in engineering applications requiring real-time processing and large-scale deployments. Cloud-based AI systems, with their elastic computational capabilities, offer a promising solution by dynamically scaling resources to meet fluctuating demands. Additionally, edge computing plays a crucial role in reducing latency and bandwidth usage by processing data locally, closer to its source. This hybrid approach, combining cloud and edge computing, ensures that resource-intensive tasks, such as real-time monitoring of smart grids, can be managed efficiently while maintaining system responsiveness [97, 98].

Moreover, privacy-preserving AI techniques, like federated learning, make it possible to train models on data from different sources without sacrificing individual privacy [20]. Setting clear policies and regulations for how data is used, and making sure they comply with international data protection standards, is also vital for building trust in AI systems [99, 100].

To address the challenges of integrating AI into existing engineering systems, it's essential to develop standardized protocols and invest in the right infrastructure [101].

Developing common standards for how data is collected, stored, and shared is crucial for making AI adoption smoother, while also ensuring data security and privacy. It's equally important to invest in scalable infrastructure that can handle large-scale AI deployment, which includes upgrading outdated systems and offering AI and engineering training for staff [102].

It's also important to put bias mitigation strategies in place for AI algorithms, like using more diverse training datasets, to make sure that AI solutions are both fair and reliable [103].

Further, there is a pressing need for consistent guidelines and frameworks to be established regarding the deployment of AI in engineering. Lacking these standardized frameworks can create issues regarding the use of AI in various sectors that require different areas to function and cooperate [102].

Going forward, one of the key areas of research will be how to integrate AI with other emerging technologies like Internet Of Things (IOT) and blockchain. Not only will this integration streamline engineering processes but it will also step up the security and transparency of AI-powered operations. Yet key challenges— namely, tackling integration and legacy systems, as well as considering privacy concerns over data —must be addressed to unlock

AI's sweeping potential in engineering.

Addressing these challenges requires a concerted effort from researchers, practitioners, and policymakers to ensure the seamless and ethical integration of AI into engineering systems.

4.1. Ethical and Social Implications:

There will, however, be significant ethical and social questions that arise with the implementation of AI into engineering. These include worries that job automation will affect jobs and the culpability of AI-based decisions, whether or not this type of technology follows ethics. Meanwhile, automation of tasks that have historically been performed by humans could lead to unemployment which in turn necessitates the development of strategies for reskilling and transitioning workforces [104].

Furthermore, decision-making processes of AI systems should be clear and make their behaviour explainable in order to retain trust towards engineers as well as stakeholders [105].

A further ethical issue is the potential bias found in AI algorithms which could lead to discrimination or unfair outcomes. In order to mitigate this, training datasets must be crafted with a careful attention to diversity [103] and anti-bias strategies in all the development stages.

In **Table 15**, all the information covered in this section is presented.

Table 15. Ethical and Social Implications.

Aspect	Details
Impact on Employment	Job displacement due to automation, need for workforce re-skilling
Accountability	Ensuring transparent and accountable AI-driven decisions
Bias in AI Algorithms	Mitigating bias through diverse training datasets and bias mitigation strategies
Examples	Ethical considerations in AI deployment, transparency and accountability measures

5. Future Prospects of AI in Engineering

The future for AI in engineering is quite simply, revolutionising and will see major breakthroughs across a number of sectors. For example, the development of AI will likely extend to other leading fields in biotechnology such as genomics and wearable devices within biomedical engineering. Such a fusion in technology could potentially bring breakthroughs to personalized medicine — where AI siphons through the real-time data off wearable sensors, and mixes them with genetic information for hyper-tailored treatment plans.

Additionally, AI is likely to play a major role in the progression of touch and feel prosthetics with semi-natural response rates as well learning how amputees move so that these devices may adapt accordingly.

Looking ahead, the temporal analysis suggests an acceleration in AI progress, driven by the interaction with emerging technologies such as blockchain and IoT. These developments: i) broaden the possible future applications of AI; ii) lay the foundation for greater scalability and security in engineering systems. In fact, future AI advancements will also focus on enhancing scalability through the integration of cloud and edge computing technologies. For instance, cloud-based platforms will support resource-intensive tasks such as large-scale simulations, while edge computing will enable real-time adjustments in engineering systems. This hybrid architecture will be critical in managing the increasing complexity and computational demands of next-generation engineering applications [106].

Figure 5 provides a detailed Gantt chart outlining the timeline for integrating AI into legacy systems and IoT-enabled smart grids.

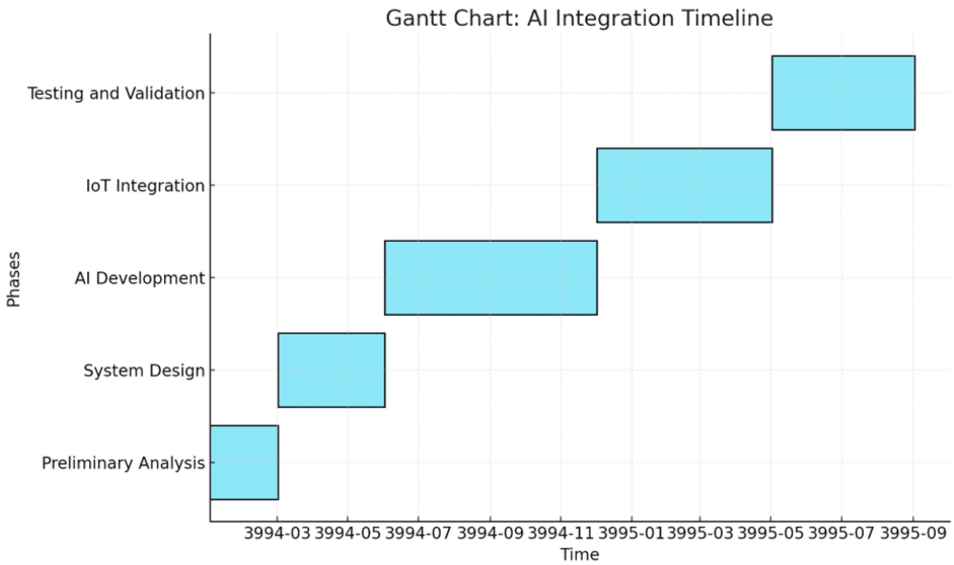

Figure 5. Gantt chart detailing the timeline for AI integration, from preliminary analysis to testing and validation.

The chart highlights key phases, including preliminary analysis, system development, and testing, offering a structured approach to overcoming integration challenges.

The future in materials science is just as exciting. AI-driven research is set to speed up the discovery of new materials with unique properties tailored to meet specific industrial needs. By combining AI with high-throughput experimentation and computational modeling, researchers can predict and create materials more efficiently [107].

This can greatly decrease the time from discovery to pressing some magic play button (e.g., in fields such as energy storage for faster materials discoveries leading to better batteries or renewable energy solutions).

Furthermore, the ability of AI to assess and forecast how materials are likely to behave and how long they could last will help in designing better and more durable structures.

Recent advances have demonstrated the transformative role of AI across multiple engineering domains:

- Chemical Engineering: Generative AI, particularly large language models (LLMs), has been pivotal in designing, scaling up, and optimizing chemical and biochemical processes. LLMs interpret complex chemical and biological data, facilitating the discovery of novel products and improving process design for sustainability [108–110].
- Materials Science: AI systems like Google's GNoME have revolutionized materials discovery by identifying over 2 million new stable inorganic crystal structures, expediting material innovation and reducing development costs [111].
- Transportation Engineering: AI enhances traffic flow prediction by integrating weather data, leading to improved safety and efficiency in connected vehicles. Additionally, AI-driven driver monitoring systems detect distracted behaviors, contributing to accident prevention [108, 111].
- Aerospace Engineering: AI applications in aeronautical engineering include fault detection in aerospace structures, utilizing AI to identify structural issues, thereby enhancing safety and maintenance efficiency [112].
- Medical Diagnostics: AI improves diagnostic accuracy through natural speech dialogue systems and automated detection methods, such as identifying microaneurysms in diabetic retinopathy, enhancing early detection and treatment [113].

With the advancement in engineering enhanced with AI, the Internet of Things and the Blockchain, there is hope for a bright future of engineering. IoT could in the future provide AI systems with constant real-time data making the insights provided by the AI systems more effective and applicable in a number of engineering steps. For example, AI systems and IoT based smart grids which are able to control the use and the distribution of electricity in real time shall make it easy to have cleaner and smarter energy systems. On the other hand, the blockchain technology is expected to guarantee the safety and accuracy of the operations of the AI especially if conducted on sensitive data and critical development infrastructure.

To realize these future prospects further analysis and experimentation is necessary. There is a need to enhance the ability and the safety of the AI system, to increase the interpretability of the AI systems as well as to support a cross disciplinary approach. It is the hope of the engineering society by addressing these issues that the overall benefits that AI will bring about will start a new era of engineering— innovative, efficient, and sustainable in every aspect and level.

6. Conclusions

There is no ambiguity regarding the fact that artificial intelligence has already brought a revolution in numerous disciplines of engineering, especially design, manufacturing, maintenance, and optimization. AI increases production as well and enhances the quality and reliability of products and services. Over time, as AI technology progresses, the role of engineering and its alternatives is likely to improve further with developing more efficient and eco-friendly solutions.

Through a comprehensive analysis of AI's current state and future potential, this study aims to serve as a guiding framework for researchers and industry professionals.

The potential for AI in engineering is tremendously great. It is expected that further studies are needed in order to solve current issues and to open other fronts. Deepening the development of AI algorithms, simplifying AI models, and enhancing AI with other modern technologies, like IoT and blockchain, is a long basic movement forward.

Telescoping the focus beyond just image recognition, it is particularly important to advance AI research in regard of building AI algorithms that are robust enough to better withstand various adversarial attacks and also cope with uncertainties one faces in a real-world scenario. Such strong AI models will help boost the trustworthiness and the overall safety of engineering systems and promote their acceptance by engineering practitioners. Also, as in other industries, it is important to ensure that AI models are more user friendly, so to say, more explainable and less of a black box. This allows engineers as well as other stakeholders to be comfortable with AI based decision making as they can appreciate and validate the decision-making process of AI which is crucial in situations where making such decisions is vital.

Always interlacing AI with the IoT and the blockchain intertwines as well, becomes another step towards deepening and enhancing engineering processes. The IoT will supply information in real time for the development of AI models and hence the accuracy and speed of making decisions will improve. As a result, it will also make the application of AI more effective as the blockchain offers protection and protection of the AI actions, which is very important in situations of extreme demand for data security and preservation. These integrations can help improve the efficiency and the security of engineering processes facilitating new inventions.

As highlighted throughout this paper, the successful application of AI in engineering requires careful selection of methodologies tailored to specific challenges and objectives. **Table 16** presents a comparative analysis of two widely used AI approaches, Deep Learning and Ensemble Methods, focusing on their application to predictive maintenance.

Table 16. Comparison Matrix: Deep Learning vs. Ensemble Methods.

	Criteria	**Deep Learning**	**Ensemble Methods**
1	Accuracy	High	Medium
2	Scalability	Medium	High
3	Robustness	High	High
4	Computational complexity	High	Medium
5	Data requirement	High	Medium

This comparison underscores the trade-offs between accuracy, scalability, and computational complexity, which are critical considerations for practical implementation.

AI can be regarded as a powerful tool in different spheres such as engineering, yet benefits extend only if certain challenges exist and are addressed. The first and most important step is to ensure the protection of privacy and security of information in the AI systems so as to prevent any cyberattacks. One other challenge is obtaining and organizing the huge volumes of data necessary for the training and validation of the systems, particularly in areas where data collection involves a lot of funds or time. Also, the challenge of enriching the content of engineering systems with artificial intelligence may be even more tedious when extensive changes in the industrial infrastructure are necessary and the willingness to change is limited.

All in all, it is possible to draw certain conclusions about the impact of Artificial Intelligence on the evolution of engineering industries concentrating on different aspects such as improved productivity in design, production, maintenance and optimization of functions. A critical analysis of existing methods for implementing AI systems was done in this study, mainly aiming at their current and further developments. As for the remainder, it is necessary to address issues associated with the privacy and security of data, the scalability of the system, and its discrimination in order for AI to remain successful.

Integrating AI with emerging technologies like IoT and blockchain offers exciting opportunities to improve the efficiency and security of engineering processes. Developing robust, transparent, and scalable AI systems, along with effective human-AI collaboration, will be crucial for fully unlocking AI's potential in engineering. By combining the strengths of AI and human expertise, collaborative AI can drive significant advancements in design, optimization, and innovation [104]. These systems can boost creativity and problem-solving by offering data-driven insights and suggesting innovative solutions.

As the field progresses, ongoing research and development will be key to overcoming current challenges and discovering new opportunities. Statistical analysis and simulation will continue to play a vital role in validating and improving AI applications, making sure they are practical and effective in real-world situations. Ultimately, the future of engineering will be shaped by how well AI technologies are integrated, leading to more innovative, efficient, and sustainable solutions.

In **Table 17**, all the information covered in this section is presented.

Table 17. Future Prospects of AI in Engineering.

Aspect	Details
Biomedical Engineering	AI with genomics and wearables, advanced prosthetics
Materials Science	AI-driven discovery and development of new materials
IoT and Blockchain Integration	Enhancing real-time data analysis and security in engineering processes
Research and Development	Addressing challenges, enhancing algorithm robustness and security, interdisciplinary collaborations

Improving the interpretability of AI models, known as explainable AI, is essential for building trust and transparency in engineering. Engineers need to understand and validate AI-driven decisions, especially in safety-critical applications. Techniques like feature importance analysis, model-agnostic interpretability methods, and visual explanations can help clarify how AI models make decisions [114]. Making AI more transparent not only builds trust among engineers and stakeholders but also helps identify and reduce potential biases in AI systems.

A promising future for AI in engineering depends on developing algorithms that can withstand adversarial attacks and handle uncertainties in real-world situations. These algorithms need to be robust, reliable, and transparent to enhance the safety and trust in AI-based engineering systems. For instance, learning-based robust control techniques can improve the resilience of autonomous control systems, ensuring they perform stably even under uncertain conditions [104].

Future research should concentrate on improving the robustness of AI algorithms, ensuring they can successfully handle uncertainties and withstand adversarial attacks. At the same time, greater transparency in AI-driven decisions will be essential to build trust and encourage the widespread adoption of these systems in critical engineering applications.

Author Contributions

Conceptualization: S.P.; Methodology: S.P.; Software: S.P.; Validation: S.P., F.P., G.Z.; Formal analysis: S.P.; Investigation: S.P., F.P., G.Z.; Resources: S.P.; Data curation: S.P.; Writing—original draft preparation: S.P., F.P.; Writing—

review and editing: S.P., F.P.; Visualization: S.P.; Supervision: S.P., G.Z.; Project administration: S.P., G.Z. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

References

1. Cao, Y.; Sheng, Q.Z.; McAuley, J.; et al. Reinforcement Learning for Generative AI: A Survey. *arXiv* **2023**, arXiv:2308.14328. [CrossRef]
2. Mahmud, M.; Kaiser, M.S.; Hussain, A.; et al. Applications of Deep Learning and Reinforcement Learning to Biological Data. *IEEE Trans. Neural Netw. Learn. Syst.* **2017**, *29*, 2063–2079. [CrossRef]
3. Mahato, N.R. Will Artificial Intelligence become alternative to Software Engineers? - A Futuristic Approach. *Rev. Rev. Index J. Multidiscip.* **2022**, *2*, 28–33. [CrossRef]
4. Simões, R.V.; Parreiras, M.V.C.; da Silva, A.C.; et al. Artificial Intelligence and Digital Transformation: Analyzing Future Trends. In Proceedings of the 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Prague, Czech Republic, 9–12 October 2022. [CrossRef]
5. Nti, I.K.; Adekoya, A.F.; Weyori, B.; et al. Applications of artificial intelligence in engineering and manufacturing: A systematic review. *J. Intell. Manuf.* **2021**, *33*, 1581–1601. [CrossRef]
6. Lv, Z.; Xie, S. Artificial intelligence in the digital twins: State of the art, challenges, and future research topics. *Dig. Twin* **2021**, *1*, 12. [CrossRef]
7. Razvi, S.; Kumar, K.; Sehgal, A.; et al. AI-Driven Optimization in Mechanical Engineering: Error Identification and System Enhancement. In *Revolutionizing the Future Trends in Mechanical Engineering*; SCIENTIFIC RESEARCH REPORTS: London, UK, 2024; pp. 67–76.
8. Rosero, R.H.L.; Silva, C.; Ribeiro, B. Remaining Useful Life Estimation in Aircraft Components with Federated Learning. *PHM Soc. Eur. Conf.* **2020**, *5*, 9. [CrossRef]
9. von Wahl, L.; Heidenreich, N.; Mitra, P.; et al. Data Disparity and Temporal Unavailability Aware Asynchronous Federated Learning for Predictive Maintenance on Transportation Fleets. *Proc. AAAI Conf. Artif. Intell.* **2024**, *38*, 15420–15428. [CrossRef]
10. Gowekar, G.S. Artificial intelligence for predictive maintenance in oil and gas operations. *World J. Adv. Res. Rev.* **2024**, *23*, 1228–1233. [CrossRef]
11. Chen, Z.; Gao, Y.; Liang, J. LOPdM: A Low-Power On-Device Predictive Maintenance System Based on Self-Powered Sensing and TinyML. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 1–13. [CrossRef]
12. Ucar, A.; Karakose, M.; Kırımça, N. Artificial Intelligence for Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends. *Appl. Sci.* **2024**, *14*, 898. [CrossRef]
13. Sani, A.R.; Zolfagharian, A.; Kouzani, A.Z. Artificial Intelligence-Augmented Additive Manufacturing: Insights on Closed-Loop 3D Printing. *Adv. Intell. Syst.* **2024**, *6*, 2400102. [CrossRef]
14. Englund, C.; Aksoy, E.E.; Alonso-Fernandez, F.; et al. AI perspectives in Smart Cities and Communities to

enable road vehicle automation and smart traffic control. *Smart Cities* **2021**, *4*, 783-802. [CrossRef]
15. Choi, W.; Na, S.; Heo, S. Integrating Drone Imagery and AI for Improved Construction Site Management through Building Information Modeling. *Buildings* **2024**, *14*, 1106. [CrossRef]
16. Aloupogianni, E.; Doctor, F.; Karyotis, C.; et al. An AI-Based Digital Twin Framework for Intelligent Traffic Management in Singapore. In Proceedings of the 2024 International Conference on Electrical, Computer and Energy Technologies (ICECET), Sydney, Australia, 25–27 July 2024. [CrossRef]
17. Shi, T.; Yang, A.; Jin, Y.; et al. Artificial intelligence in process systems engineering. In *Applications of Artificial Intelligence in Process Systems Engineering*; Ren, J., Shen, W., Man, Y., Dong, L., Eds.; Elsevier: New York, NY, USA, 2021; pp. 1–10. [CrossRef]
18. Alex, B.; Jignasa, G.; Madhubabu, K.; et al. AI-Driven Smart Irrigation: Enhancing Agricultural Water Efficiency Through Intelligent Valve Regulation in Piped and Micro Irrigation Networks. In Proceedings of the 2024 First International Conference on Pioneering Developments in Computer Science & Digital Technologies (IC2SDT), Delhi, India, 2–4 August 2024. [CrossRef]
19. Liu, Z.; Zhou, J.; Yang, X. Research on Water Resource Modeling Based on Machine Learning Technologies. *Water* **2024**, *16*, 472. [CrossRef]
20. Kethireddy, R.R. Privacy-Preserving AI Techniques for Secure Data Sharing in Healthcare. *J. Recent Trends Comput. Sci. Eng.* **2020**, *8*, 41–51. [CrossRef]
21. Mondal, T.G.; Chen, G. Artificial intelligence in civil infrastructure health monitoring—Historical perspectives, current trends, and future visions. *Front. Built. Environ.* **2022**, *8*. [CrossRef]
22. Ricciardi Celsi, L.; Valli, A. Applied Control and Artificial Intelligence for Energy Management: An Overview of Trends in EV Charging, Cyber-Physical Security and Predictive Maintenance. *Energies* **2023**, *16*, 4678. [CrossRef]
23. Kumar, M.; Patra, B. Smart Grid Technologies: A Comprehensive Review. *Turk. J. Comput. Math. Educ. (TURCOMAT)* **2020**, *11*, 2895–2899. [CrossRef]
24. Yousef, L.A.; Yousef, H.; Rocha-Meneses, L. Artificial Intelligence for Management of Variable Renewable Energy Systems: A Review of Current Status and Future Directions. *Energies* **2023**, *16*, 8057. [CrossRef]
25. Ali, J.M. AI-driven software engineering. *Adv. Eng. Innov.* **2023**, *3*, 17–21. [CrossRef]
26. Raslan, W.; El Sherbiny, Z.A.; Mohamed, M.s.; et al. Smart Vehicle Safety: AI-Driven Driver Assistance and V2X Communications. In Proceedings of the 2024 International Telecommunications Conference (ITC-Egypt), Cairo, Egypt, 22–25 July 2024; pp. 787–792. [CrossRef]
27. Harriss, D.; Sheh, R.; Geappen, K. Autonomous Aerial Drones Connecting Public Safety: Opportunities and Challenges for the Future. In Proceedings of the Autonomous Aerial Drones Connecting Public Safety: Opportunities and Challenges for the Future, San Diego, CA, USA, 22–25 April 2024. [CrossRef]
28. Khaleel, M.; Ahmed, A.; Alsharif, A. Artificial Intelligence in Engineering. *Brill. Res. Artif. Intell.* **2023**, *3*, 32–42. [CrossRef]
29. Li, W. The application of artificial intelligence in aerospace engineering. *Appl. Comput. Eng.* **2024**, *35*, 17–25. [CrossRef]
30. Sinha, P.C.; Singh, M. AI and Robotics in Space Exploration: Exploring the Unknown with Intelligent Machines. *Int. J. Emerg. Technol. Innov. Res.* **2019**, *6*, 230–241. [CrossRef]
31. Swan, R.M.; Atha, D.; Leopold, H.A.; et al. AI4MARS: A Dataset for Terrain-Aware Autonomous Driving on Mars. In Proceedings of the 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Nashville, TN, USA, 19–25 June 2021. [CrossRef]
32. Park, H.; Ono, M. Sequential Deep Learning for Mars Autonomous Navigation. In Proceedings of the 2023 IEEE Space Computing Conference (SCC), Pasadena, CA, USA, 18–21 July 2023. [CrossRef]
33. Deshpande, R.S.; Ambatkar, P.V. Interpretable Deep Learning Models: Enhancing Transparency and Trustworthiness in Explainable AI. *Ciênc. Eng. - Sci. Eng. J.* **2023**, *11*, 1352–1363. [CrossRef]
34. Saeed, W.; Omlin, C. Explainable AI (XAI): A Systematic Meta-Survey of Current Challenges and Future Opportunities. *Knowl.-Based Syst.* **2021**, *263*, 110273. [CrossRef]
35. Tedeschini, B.C.; Savazzi, S.; Stoklasa, R.; et al. Decentralized Federated Learning for Healthcare Networks: A Case Study on Tumor Segmentation. *IEEE Access* **2022**, *10*, 8693–8708. [CrossRef]
36. Elayan, H.; Aloqaily, M.; Guizani, M. Sustainability of Healthcare Data Analysis IoT-Based Systems Using Deep Federated Learning. *IEEE Internet Things J.* **2021**, *9*, 7338–7346. [CrossRef]
37. Hebecker, M.; Lambrecht, J.; Schmitz, M. Towards Real-World Force-Sensitive Robotic Assembly through Deep Reinforcement Learning in Simulations. In Proceedings of the 2021 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM), Delft, The Netherlands, 12–16 July 2021. [CrossRef]

38. Farooq, A.; Iqbal, K. A Survey of Reinforcement Learning for Optimization in Automation. In Proceedings of the 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE), Bari, Italy, 28 August–1 September 2024. [CrossRef]
39. Liu, Q.; Gu, J.; Yang, J.; et al. Cloud, Edge, and Mobile Computing for Smart Cities. In *Urban Informatics*; Shi, W., Goodchild, M.F., Batty, M., et al., Eds.; Springer: Singapore, 2021; pp. 757–795. [CrossRef]
40. Peyman, M.; Copado, P.; Tordecilla, R.D.; et al. Edge Computing and IoT Analytics for Agile Optimization in Intelligent Transportation Systems. *Energies* **2021**, *14*, 6309. [CrossRef]
41. SAE. Generative Design in Aerospace and Automotive Structures. *SAE Research Report EPR2024016*, 23-07-2024. SAE: Detroit, MI, USA. [CrossRef]
42. SAE. Towards the Design-Driven Carbon Footprint Reduction of Composite Aerospace and Automotive Components: An Overview. *SAE Technical Paper Series*. *SAE Technical Paper 2024-37-0032*, 12-06-2024. SAE: Detroit, MI, USA. [CrossRef]
43. Maataoui, S.; Bencheikh, G. Predictive Maintenance in the Industrial Sector: A CRISP-DM Approach for Developing Accurate Machine Failure Prediction Models. In Proceedings of the 2023 Fifth International Conference on Advances in Computational Tools for Engineering Applications (ACTEA), Zouk Mosbeh, Lebanon, 5–7 July 2023. [CrossRef]
44. Koca, O.; Kaymakci, O.; Mercimek, M. Advanced Predictive Maintenance with Machine Learning Failure Estimation in Industrial Packaging Robots. In Proceedings of the 2020 International Conference on Development and Application Systems (DAS); Suceava, Romania, 21–23 May 2020. [CrossRef]
45. Ohalete, N.C.; Aderibigbe, A.O.; Ani, E.C.; et al. Advancements in Predictive Maintenance in the Oil and Gas Industry: A Review of AI and Data Science Applications. *World J. Adv. Res. Rev.* **2023**, *20*, 167–181. [CrossRef]
46. Latrach, A. Application of Deep Learning for Predictive Maintenance of Oilfield Equipment [Master's Thesis]. 2020. [CrossRef]
47. Gadaleta, M.; Pellicciari, M.; Berselli, G. Optimization of the Energy Consumption of Industrial Robots for Automatic Code Generation. *Robot. Comput. Integr. Manuf.* **2019**, *57*, 452–464. [CrossRef]
48. Carabin, G.; Wehrle, E.; Vidoni, R. A Review on Energy-Saving Optimization Methods for Robotic and Automatic Systems. *Robotics* **2017**, *6*, 39. [CrossRef]
49. Nurhaeni, H.; Delhi, A.; Daeli, O.P.M.; et al. Optimizing Electrical Energy Use through AI: An Integrated Approach for Efficiency and Sustainability. *IEEE Trans. Artif. Intell.* **2024**, *2*, 106–113. [CrossRef]
50. Mishra, S. Artificial Intelligence versus Food Processing and Manufacturing Sector: An Editorial. *Open Access J. Data Sci. Artif. Intell.* **2024**, *2*, 1–4. [CrossRef]
51. Jadhav, N.R.; Bhutada, S.; Sagavkar, S.R.; et al. AI-Driven Pharmaceutical Manufacturing: Revolutionizing Quality Control and Process Optimization. *J. Stat. Manag. Syst.* **2024**, *27*, 405–416. [CrossRef]
52. Muniandi, B.; Maurya, P.K.; Bhavani, C.H.; et al. AI-Driven Energy Management Systems for Smart Buildings. *Power Syst. Technol.* **2024**, *48*, 322–337. [CrossRef]
53. Merabet, G.H.; Essaaidi, M.; Haddou, M.; et al. Intelligent Building Control Systems for Thermal Comfort and Energy-Efficiency: A Systematic Review of Artificial Intelligence-Assisted Techniques. *Renew. Sustain. Energy Rev.* **2021**, *144*, 110969. [CrossRef]
54. Santhiya, P.; Jebadurai, I.; Paulraj, G.; et al. ITS-AI Integration: Enhanced Strategies for Mitigating Urban Traffic Congestion. In Proceedings of the 2024 5th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), Jamshedpur, India, 9–10 April 2024. [CrossRef]
55. Ogundipe, O.B.; Okwandu, A.C.; Abdulwaheed, S.A. Optimizing Construction Supply Chains Through AI: Streamlining Material Procurement and Logistics for Project Success. *GSC Adv. Res. Rev.* **2024**, *20*, 147–158. [CrossRef]
56. Ming, L.W.; Anderson, J.; Hidayat, F.; et al. AI as a Driver of Efficiency in Waste Management and Resource Recovery. *Int. Trans. Artif. Intell.* **2024**, *2*, 128–134. [CrossRef]
57. Hussain, M.; Karthikeyan, N.; Maurya, I.; et al. AI-Optimized Irrigation for Sustainable Agriculture. In Proceedings of the 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), Chennai, India, 18–19 April 2024. [CrossRef]
58. Yue, W.; Chen, L.; Huang, H. Research on Machine Learning Algorithm-Based Approach for Detecting Abnormal Data from Environmental Sensors in Different Dimensions. In Proceedings of the 2023 International Joint Conference on Robotics and Artificial Intelligence, Shanghai, China, 7–9 July 2023; pp. 26–33. [CrossRef]
59. Mahardhika, S.; Putriani, O. Deployment and Use of Artificial Intelligence (AI) in Water Resources and Water Management. *IOP Conf. Ser. Earth Environ. Sci.* **2023**, *1195*, 012056. [CrossRef]

60. Krishnan, R.; Ashokkumar, C.; Nithila, E.E.; et al. AI-Powered Demand Response Mechanisms for Sustainable Smart Grids. In Proceedings of the 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 7–9 August 2024. [CrossRef]
61. Udo, W.S.; Kwakye, J.M.; Ekechukwu, D.E.; et al. Smart Grid Innovation: Machine Learning for Real-Time Energy Management and Load Balancing. *Eng. Sci. Technol. J.* **2023**, *4*, 603–616. [CrossRef]
62. Hameed, Z.; Hashemi, S.; Træholt, C. Applications of AI-Based Forecasts in Renewable Based Electricity Balancing Markets. In Proceedings of the 2021 22nd IEEE International Conference on Industrial Technology (ICIT), Valencia, Spain, 10–12 March 2021. [CrossRef]
63. Joshi, A.; Spilbergs, A.; Miķelsone, E. AI-Enabled Drone Autonomous Navigation and Decision Making for Defence Security. *Environ. Technol. Resour.* **2024**, *4*, 138–143. [CrossRef]
64. Kalidas, A.P.; Joshua, C.J.; Quadir, A.; et al. Deep Reinforcement Learning for Vision-Based Navigation of UAVs in Avoiding Stationary and Mobile Obstacles. *Drones* **2023**, *7*, 245. [CrossRef]
65. Zhang, G.; Raina, A.; Cagan, J.; et al. A cautionary tale about the impact of AI on human design teams. *Des. Stud.* **2021**, *72*, 100990. [CrossRef]
66. Goodall, R.E.A. Accelerating Materials Discovery with Machine Learning [Apollo - University of Cambridge Repository]. 2021. [CrossRef]
67. Taterao, K.S.; Anant, M.A.; Sanjay, M.G.; et al. Construction of Green Buildings by using AI in the Civil Engineering Field. *Int. J. Res. Appl. Sci. Eng. Technol.* **2023**, *11*, 1912–1918. [CrossRef]
68. Xu, Y.; Qian, W.; Li, N.; Li, H. Typical advances of artificial intelligence in civil engineering. *Adv. Struct. Eng.* **2022**, *25*, 3405–3424. [CrossRef]
69. Czumbil, L.; Micu, D.; Ceclan, A. Advanced Numerical Methods Based on Artificial Intelligence. In *Numerical Methods for Energy Applications*; Mahdavi Tabatabaei, N., Bizon, N., Eds.; Springer: Cham, Switzerland, 2021. [CrossRef]
70. Murthy, N.M. Future Scope of Artificial Intelligence in Software Engineering. *Int. J. Sci. Res.* **2023**, *12*, 1401–1402. [CrossRef]
71. Barenkamp, M.; Rebstadt, J.; Thomas, O. Applications of AI in classical software engineering. *AI Perspect. Adv.* **2020**, *2*, 1–15. [CrossRef]
72. Kadkhodayi, A.; Jabeli, M.; Aghdam, H. Artificial Intelligence-Based Real-Time Traffic Management. *J. Electr. Electron. Eng.* **2023**, *2*, 368–373.
73. Mahmoud, A.; Abdelhady, K.; Salama, M. New Algorithm for Vehicle-to-Vehicle Advanced Driver-Assistance Systems (V2V-ADAS) to Prevent Collisions. *Int. Uni-Sci. Res. J.* **2022**, *3*, 133–138. [CrossRef]
74. Noviati, N.; Putra, F.; Sadan, S.; et al. Artificial Intelligence in Autonomous Vehicles: Current Innovations and Future Trends. *Int. J. Cyber IT Service Manag.* **2024**, *4*, 97–104. [CrossRef]
75. Thon, C.; Finke, B.; Kwade, A.; et al. Artificial Intelligence in Process Engineering. *Adv. Intell. Syst.* **2021**, *3*, 2000261. [CrossRef]
76. Wang, J.; Hu, J.; Mills, J.; et al. Federated Ensemble Model-Based Reinforcement Learning in Edge Computing. *IEEE Trans. Parallel Distrib. Syst.* **2021**, *34*, 1848–1859. [CrossRef]
77. Wang, C.; Yao, T.; Fan, T.; et al. Modeling on Resource Allocation for Age-Sensitive Mobile-Edge Computing Using Federated Multiagent Reinforcement Learning. *IEEE Internet Things J.* **2024**, *11*, 3121–3131. [CrossRef]
78. Combining Federated Learning and Control: A Survey. Available from: https://arxiv.org/abs/2407.11069 (cited 28 February 2025).
79. Keremer, O.; Malay, F.C.; Deveci, B.; et al. Optimisation of a Chemical Process by Using Machine Learning Algorithms with Surrogate Modeling. In: Younas, M., Awan, I., Grønli, T.M. (Eds.). *Mobile Web and Intelligent Information Systems*. MobiWIS 2023. Lecture Notes in Computer Science, vol 13977. Springer: Cham, Switzerland, 2023. [CrossRef]
80. Hajjar, Z.; Tayyebi, S.; EghbalAhmadi, M. Application of AI in Chemical Engineering. *Artif. Intell.- Emerg. Trends Appl.* 2018. [CrossRef]
81. Human-Centered AI. Available from: https://www.semanticscholar.org/paper/Human-Centered-AI-Barmer-Dzombak/264b9b136889da3b4d7e50ef58c77678b35dc3e0 (cited 5 March 2025).
82. Baughan, N.; Douglas, L.; Giger, M.L. Past, Present, and Future of Machine Learning and Artificial Intelligence for Breast Cancer Screening. *J. Breast Imaging* **2022**, *4*, 451–459. [CrossRef]
83. Chopra, S.; Emran, T.B. Advances in AI-based prosthetics development: editorial. *Int. J. Surg. (Lond, Engl.)* **2024**, *110*, 4538–4542. [CrossRef]

84. Wala, H.Z.; Nevagi, T.P.; Jagtap, S. Revolutionizing Healthcare: Early Disease Detection through Retinal Imaging and AI-Driven Approaches. In Proceedings of the 2023 6th International Conference on Advances in Science and Technology (ICAST), Mumbai, India, 8–9 December 2023. [CrossRef]
85. Doudican, N.A.; Kumar, A.; Singh, N.K.; et al. Personalization of cancer treatment using predictive simulation. *J. Transl. Med.* **2015**, *13*, 43. [CrossRef]
86. Yang, X. The applications of artificial intelligence in personalized medicine. *Appl. Comput. Eng.* **2024**. [CrossRef]
87. Ozkaya, I. What Is Really Different in Engineering AI-Enabled Systems? *IEEE Softw.* **2020**, *37*, 3–6. [CrossRef]
88. Anand, A.; Goel, S.; Panesar, G.S. Energy-Efficient Edge Computing Architectures for AI Workloads: A Comparative Analysis in Cloud-Driven Environments. In Proceedings of the 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP), Sonipat, India, 25–26 May 2024. [CrossRef]
89. Talirz, L.; Kumbhar, S.; Passaro, E.; et al. Materials Cloud, a Platform for Open Computational Science. *Sci. Data* **2020**, *7*, 229. [CrossRef]
90. Bhandari, U.; Chen, Y.; Ding, H.; et al. Machine-Learning-Based Thermal Conductivity Prediction for Additively Manufactured Alloys. *J. Manuf. Mater. Process* **2023**, *7*, 160. [CrossRef]
91. Chen, E.S.; Ahmadianshalchi, A.; Sparks, S.S.; et al. Machine Learning Enabled Design and Optimization for 3D-Printing of High-Fidelity Presurgical Organ Models. *Adv. Mater. Technol.* **2025**, *10*, 2400037. [CrossRef]
92. Abhishek, V.A.; Binny, S.; Johan, T.R.; et al. Federated Learning: Collaborative Machine Learning without Centralized Training Data. *Int. J. Eng. Technol. Manag. Sci.* **2022**, *6*, 355–359. [CrossRef]
93. El Houda, Z.A.; Moudoud, H.; Brik, B. Federated Deep Reinforcement Learning for Efficient Jamming Attack Mitigation in O-RAN. *IEEE Trans. Veh. Technol.* **2024**, *73*, 9334–9343. [CrossRef]
94. Zaw, C.W.; Pandey, S.R.; Kim, K.; et al. Energy-Aware Resource Management for Federated Learning in Multi-Access Edge Computing Systems. *IEEE Access* **2021**, *9*, 34938–34950. [CrossRef]
95. Tang, Y.; Du, G.; Long, J.; et al. Integration of Online Deep Reinforcement Learning and Federated Learning: A Dynamic Energy Management Strategy for Industrial Applications. *IET Commun.* **2023**, *17*, 2162–2177. [CrossRef]
96. Tantithamthavorn, C.; Jiarpakdee, J. Explainable AI for Software Engineering. In Proceedings of the 2021 36th IEEE/ACM International Conference on Automated Software Engineering (ASE), Melbourne, Australia, 15–19 November 2021. [CrossRef]
97. Jiang, J.; Xin, P.; Wang, Y.; et al. A Priority-Based Online Container Placement Strategy for 5G MEC Cloud Enabled Smart Grid. In Proceedings of the 2022 IEEE 23rd International Conference on High Performance Switching and Routing (HPSR), Taicang, China, 6–8 June 2022. [CrossRef]
98. Wang, T.; Jiang, Y.; Zhao, K.; et al. Energy-Efficient Edge-Cloud Collaborative Intelligent Computing: A Two-Timescale Approach. In Proceedings of the 2022 IEEE International Conference on Services Computing (SCC), Barcelona, Spain, 10–16 July 2022. [CrossRef]
99. Bhandari, K.; Kumar, K.; Sangal, A.L. Artificial Intelligence in Software Engineering: Perspectives and Challenges. In Proceedings of the 2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC), Jalandhar, India, 26–28 May 2023. [CrossRef]
100. Dalpiaz, F.; Niu, N. Requirements Engineering in the Days of Artificial Intelligence. *IEEE Softw.* **2020**, *37*, 7–10. [CrossRef]
101. Ahmad, K. Human-centric Requirements Engineering for Artificial Intelligence Software Systems. In Proceedings of the 2021 IEEE 29th International Requirements Engineering Conference (RE), Notre Dame, IN, USA, 20–24 September 2021. [CrossRef]
102. Dzhusupova, R.; Bosch, J.; Olsson, H. Challenges in developing and deploying AI in the engineering, procurement and construction industry. In Proceedings of the 2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC), Los Alamitos, CA, USA, 27 June–1 July 2022; pp. 1070–1075. [CrossRef]
103. Waller, M.; Rodrigues, O.; Lee, M.; et al. Bias Mitigation Methods: Applicability, Legality, and Recommendations for Development. *J. Artif. Intell. Res.* **2024**, *81*, 1043–1078. [CrossRef]
104. Lelkó, A.; Németh, B.; Gáspár, P. Reinforcement Learning-Based Robust Vehicle Control for Autonomous Vehicle Trajectory Tracking. *Eng. Proc.* **2024**, *79*, 30. [CrossRef]
105. Lo, D. Human-Centered AI for Software Engineering: Requirements, Reflection, and Road Ahead. In Proceedings of the 16th Innovations in Software Engineering Conference, Allahabad, India, 23–25 February 2023; p. 1. [CrossRef]
106. Firouzi, F.; Farahani, B.J.; Marinšek, A. The Convergence and Interplay of Edge, Fog, and Cloud in the AI-

Driven Internet of Things (IoT). *Inf. Syst.* **2021**, *107*, 101840. [CrossRef]
107. Li, G.; Wang, X.; Li, M. A Review of Recent Trends and Industry Prospects for Artificial Intelligence Technologies. In Proceedings of the 2021 8th International Conference on Behavioral and Social Computing (BESC), Doha, Qatar, 29–31 October 2021.
108. Decardi-Nelson, B.; Alshehri, A.; You, F. Generative artificial intelligence in chemical engineering spans multiple scales. *Front. Chem. Eng.* **2024**, *6*, 1458156. [CrossRef]
109. Anstine, D.; Isayev, O. Generative Models as an Emerging Paradigm in the Chemical Sciences. *J. Am. Chem. Soc.* **2023**, *145*, 8736–8750. [CrossRef]
110. Back, S.; Aspuru-Guzik, A.; Ceriotti, M.; et al. Accelerated chemical science with AI. *Dig. Discov.* **2024**, *3*, 23–33. [CrossRef]
111. Scheffler, M. AI guided workflows for efficiently screening the materials space. *Coshare Sci.* **2024**, *2*, 2. [CrossRef]
112. Schweidtmann, A. Mining Chemical Process Information from Literature for Generative Process Design: A Perspective. *Syst. Control Trans.* **2024**, *3*, 84–91. [CrossRef]
113. Yuriy, R.; Tatarina, O.; Kaminskyy, V.; et al. Modern Methods and Prospects for Using Artificial Intelligence in Disease Diagnostics: A Narrative Review. *Futur. Med.* **2024**, *3*, 11–24. [CrossRef]
114. Ribeiro, M.; Singh, S.; Guestrin, C. Why should I trust you? Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; pp. 1135–1144. [CrossRef]