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ENGINEERING OF THE FUTURE: COMBINING BIG DATA, ANALYTICS AND ARTIFICIAL INTELLIGENCE TO DEVELOP SUSTAINABLE TECHNOLOGICAL SOLUTIONS

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ABSTRACT

Purpose: This paper aims to critically review the integration of big data analytics and AI in engineering systems for addressing climate change, energy efficiency and resource optimisation, and to identify the key barriers to their wider adoption.

Design/Methodology/Approach: The study adopts a qualitative research methodology based on secondary data analysis of 17 peer-reviewed articles published between 2016 and 2026, using thematic analysis to identify key trends and patterns.

Research Limitation: Challenges associated with implementing the described systems include high costs and data security concerns, indicating the need for further research on secure and cost-effective implementation.

Findings: Big Data, Analytics, and Artificial Intelligence (AI) can enhance engineering decision-making by improving sustainability and efficiency. Data-driven methods are used to monitor and optimise industrial processes, with lower energy usage and waste. Predictive analysis reduces downtime and equipment failures using machine learning.

Practical Implication: The combined use of digital technologies supports resource optimisation, environmental monitoring through carbon footprint tracking and climate modelling, and the transformation of traditional reactive engineering systems into proactive and autonomous systems.

Social Implication: AI- and Big Data-related solutions improve smart cities, transportation systems, and buildings through traffic flow reduction, lower emissions, and more sustainable urban planning.

Originality/Value: Unlike application-specific studies, this article contributes to knowledge by synthesising big data, analytics, and AI applications in engineering into five cross-cutting themes and outlining conditions for their sustainability effect, such as integration with cyber-physical systems.

Keywords: *Artificial intelligence. big data. climate change. engineering systems. sustainability*

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INTRODUCTION

Engineering in the digital age has been fundamentally shaped by the rapid development of data-driven technologies such as big data, analytics, and artificial intelligence (AI). Conventional engineering methods, in which many processes used to be highly deterministic and manual-intensive, are gradually being replaced by intelligent, adaptable systems that can process large volumes of data in real time (Apata et al., 2026; Rani et al., 2026). This shift is directly linked to the emergence of Industry 4.0, in which cyber-physical devices, the Internet of Things (IoT), and advanced analytics are integrated to streamline engineering operations and achieve engineering outcomes (Hector & Panjanathan, 2024; Xu et al., 2018).

Big data is an essential component of any contemporary engineering system because it allows engineers to collect, store, and analyse large volumes of data from sensors, machines, and digital platforms (Hashem et al., 2015). Similarly, machine learning and deep learning are AI-based technologies that improve prediction, automation, and decision-making across engineering processes (Jordan & Mitchell, 2015). Analytics also bridges the gap between raw data and actionable insights, helping engineers work more efficiently, reduce costs, and improve system performance (Boldosova, 2019).

Meanwhile, global sustainability issues (climate change, energy shortages, resource scarcity, and more) have created a clear demand for new engineering solutions (United Nations, 2015). Engineering systems account for a large share of global energy use and carbon emissions, so transforming them is essential to achieve sustainable growth goals (International Energy Agency, 2021). As a result, big data, AI, and analytics in engineering are increasingly seen as ways to achieve sustainable technological development (Vinuesa et al., 2020).

Despite the rapid development of digital technologies, a significant gap remains between the objectives of technological innovation and sustainability (Herasymchuk et al., 2025b). Engineering systems often implement big data and artificial intelligence (AI) solutions with the aim of efficiency and economic benefits, with little regard to the environment and society. Also, the lack of unified frameworks to integrate big data, analytics, AI, and sustainability-focused engineering settings limits the potential of these technologies to help resolve various global issues (Zhang et al., 2026). This lack of interaction shows the need for a more comprehensive approach that treats sustainable development principles as the starting point for technological development.

This paper aims to critically review the integration of big data analytics and AI in engineering systems to address climate change, energy efficiency, and resource optimisation, and to identify the key barriers to their wider adoption. The study aims to examine current applications of big data, analytics, and AI in engineering systems; identify the benefits of these technologies in promoting sustainability; and determine the barriers to using AI in engineering.

This study may contribute to the literature on digital transformation in engineering by focusing on incorporating advanced technologies that can support sustainable outcomes. It offers insights into how engineering innovation can support the United Nations Sustainable

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Development Goals (SDGs), especially clean energy, sustainable cities, and responsible consumption (United Nations, 2015). In addition, the results can inform policymakers and industry players seeking approaches that use AI and big data to achieve sustainable development (OECD, 2019).

LITERATURE REVIEW

Theoretical Foundations

The application of big data, analytics, and AI in engineering is based on several theoretical models, such as systems theory, digital transformation theory, and sustainable engineering theory (Herasymchuk et al., 2025a). In engineering systems, systems theory focuses on the interrelation of components, emphasising the importance of a holistic approach to problem-solving (Meadows, 2008). This view is especially applicable to sustainability, which is complex because it involves environmental, economic, and social factors.

Digital transformation theory offers a framework for understanding how new technologies are transforming industries and organisational practices (Vial, 2019). Digital transformation is the integration of data and technology to increase efficiency, innovation, and competitiveness in engineering. Sustainable engineering models, in turn, focus on creating systems that minimise environmental impact while maximising benefits to resources and society (Dincer & Rosen, 2017). Together, these theories provide a basis for how integrating technologies can facilitate sustainable development.

Big Data in Engineering

The large volume, speed, and diversity that define "big data" permit engineers to evaluate complex and dynamic engineering systems (Laney, 2001). In addition, in an engineering context, there are many different places where "big data" can be obtained, such as sensors on equipment or machines and digital platforms. These provide valuable performance and behavioural data for the system (Hashem et al., 2015).

Big Data supports the evaluation of the condition of various types of infrastructure, anticipating potential maintenance activities and improving both cost-effectiveness and safety through its application in managing infrastructures (Lacey et al., 2021). Furthermore, big data allows for optimisation of production processes and quality control in manufacturing, creating a "smart factory" environment (Wang et al., 2016). Additionally, big data facilitates the integration of renewable energy into the energy grid and optimises the management of the grid itself (Zhang et al., 2018). Overall, these applications illustrate the role of big data in the engineering profession.

Role of Analytics

Analytics is important in applying raw data to generate actionable information about engineering decisions. Descriptive analytics aims at comprehending past data, whereas predictive analytics applies statistical methods and machine learning in order to predict the

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future (Boldosova, 2019). Prescriptive analytics takes an extra step and suggests the best course of action, which is founded on data-driven knowledge (Delen & Zolbanin, 2018).

Applications in engineering systems. In engineering systems, analytics is commonly used in the areas of optimisation, risk management, and performance enhancement. As an example, predictive analytics can detect possible equipment failures and provide proactive maintenance, and decrease downtime (Lee et al., 2018). Similarly, prescriptive analytics can optimise resource allocation and energy consumption, supporting sustainability targets (Dumlao & Ishihara, 2020). Applying analytics to engineering supports decision-making and enables the creation of efficient, sustainable systems.

Artificial Intelligence in Engineering

Artificial intelligence has become a primary source of innovation in engineering, enabling smart systems that can acquire knowledge, adapt, and make independent decisions (Jordan & Mitchell, 2015). Machine learning algorithms can compute trends and draw predictions based on huge datasets, and deep learning algorithms can be used to conduct more advanced tasks (image recognition and natural language processing) (LeCun et al., 2015).

AI can be used in different engineering fields, such as robotics, autonomous systems, and smart infrastructure. In the same case, transport systems are being optimised through AI and improved in terms of traffic jams and emissions (Vinuesa et al., 2020). The applications of AI in construction include better management of the project and evaluation of risks, increasing efficiency, and minimising wastage (Oesterreich & Teuteberg, 2016). These applications suggest that AI could change engineering practices and play a role in sustainable development.

Integration for Sustainability

A combination of big data, analytics, and AI is mandatory in coming up with solutions in engineering that are sustainable. Such technologies allow managing the resources within the city, such as energy, water, and transportation systems, efficiently in the smart city (Bibri & Krogstie, 2017). As an example, data-driven systems are able to optimize traffic movement, reduce traffic congestion, and carbon emissions.

In renewable energy technology, AI and analytics enhance the effectiveness and consistency of energy collection and distribution (Zhang et al., 2018). Energy demand and supply can be predicted by the use of forecasting models, making it easy to incorporate renewable sources into the grid. Also, the principle of the circular economy accentuates reuse and recycling of materials, which is backed by the data-driven technologies that monitor the movement of materials and enhance the use of resources (Geissdoerfer et al., 2017). These examples demonstrate that the implementation of innovative technologies can help to solve sustainability issues and ensure an environmentally friendly approach to engineering activities.

Gaps in Literature

Although the current literature has improved significantly, several gaps remain. First, the integration of engineering, data science, and sustainability studies remains interdisciplinary,

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which constrains the development of holistic solutions (Zhang et al., 2026). Second, qualitative research on the broader implications of technology integration remains limited because most studies rely on quantitative analysis. Third, the field needs structures that formally connect big data, analytics, and AI with sustainable engineering concepts. These gaps are critical for future research and practice because they will support the development of more comprehensive and effective engineering solutions that meet global sustainability goals.

Theoretical background and identified gaps

The literature review shows that research on the integration of big data, analytics, and artificial intelligence into engineering systems relies on three key theoretical approaches, which, however, are rarely combined in a single analytical framework. Systems theory (Krap et al., 2024; Lysenko et al., 2024) explains the interdependence of components of engineering systems, but does not take into account the digital dimension of transformation provided by big data and AI.

Digital transformation theory (Stender et al., 2024; Shevchenko et al., 2023) describes how technologies change industry practices, but leaves out environmental and social sustainability criteria. Sustainable engineering models (Arsawan et al., 2024; Bielialov et al., 2023) focus on minimising environmental impact, but do not offer specific mechanisms for combining digital tools with sustainable development goals. Thus, the main gap is the lack of a holistic conceptual model that simultaneously integrates the technological capabilities of big data, analytics, and AI with the principles of systems thinking and sustainability engineering. In addition, there is a lack of qualitative syntheses that summarise the interdisciplinary connections between these technologies across different engineering disciplines. It is to fill these gaps that this study is dedicated.

MATERIALS AND METHODS

Research Design

This study is based on a qualitative research methodology to determine the aspects of applying big data, analytics, and artificial intelligence (AI) in the design of sustainable solutions in engineering. A qualitative design will be more suitable in the current study because it allows for analysing the underlying complex technological processes in detail and their impacts on sustainability (Creswell & Poth, 2018). This paper is exploratory and interpretive research, according to which it is possible to make observations of patterns, relationships, and new themes in the literature that exist today (Saunders et al., 2019).

The descriptive quality of the study is explained by the dynamic nature of the research topic, with its interdisciplinary nature, where technologies and environmental and social issues collide. The analysis of the different studies conceptualising and using big data, analytics, and AI in the context of engineering, specifically with regard to their sustainability outcomes, is based on an interpretive approach (Koval et al., 2023; Bryman, 2016). This paradigm can help us construct a holistic view of how digital technologies can be used in sustainable engineering.

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Data Source

The study is based on secondary data collected from peer-reviewed research articles published between 2016 and 2026. The analysis of secondary data will be appropriate to disseminate the already known information and define patterns in various studies (Johnston, 2017). The limited time frame will make sure that the analysis records the recent trends in big data, analytics, and AI, which are dynamic disciplines.

The academic databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect, were identified for use as the source of data. These databases were selected based on their comprehensive coverage of high-quality research in engineering, computer science and sustainability (Mongeon & Paul-Hus, 2016), which provide rigorously reviewed research with a representative sample size from which to analyse, due to the wide array of databases that are being used to expand the content of this literature review. The final sample comprised 17 peer-reviewed articles. Their findings are synthesised in the five themes of the Results section. The key studies of each theme are summarised in Tables 1–5, which also include a report of the International Energy Agency (2021).

Inclusion and Exclusion Criteria

In making sure that the selected studies were relevant and of good quality, there were certain inclusion and exclusion criteria.

The inclusion criteria were as follows:

- peer-reviewed journal articles focusing on big data, analytics, or AI within engineering contexts;
- studies that explicitly address sustainability, including environmental, economic, or social dimensions;
- articles published in English between 2016 and 2026.

The exclusion criteria included:

- opinion papers, editorials, and non-peer-reviewed publications;
- studies that do not focus on engineering applications, such as purely social or business contexts;
- articles lacking sufficient methodological detail or empirical evidence.

The criteria were used to make sure that the chosen studies were relevant, credible, and consistent with the objectives of the research (Petticrew & Roberts, 2015).

Data Collection Procedure

The data gathering procedure was a systematic and structured one based on the PRISMA (Preferred Reporting Items to Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021). An extensive search strategy was elaborated in order to identify relevant studies using keywords. The search terms were mainly “big data” AND “engineering” AND “sustainability”, “artificial intelligence” AND “sustainable systems”, “data analytics” AND “engineering sustainability”.

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In the first search, a significant number of articles were obtained, and they were filtered by the titles and abstracts to discard all irrelevant studies. Full-text screening was then done to determine the eligibility of the rest of the articles based on the preset inclusion and exclusion criteria. During the screening, duplicate records were eliminated to improve accuracy.

The dataset on which the analysis was done was the final selection of studies. The data collection system increases the clarity and repeatability of the research process (Moher et al., 2015).

Data Analysis Method

The data obtained underwent thematic analysis, which is a commonly used qualitative approach to identifying patterns in data, analysing data, and reporting the patterns (Braun & Clarke, 2006). Various phases were identified in the analysis process, which included familiarisation with the data, coding, theme development, and interpretation.

To begin with, the chosen articles have been examined in detail to establish essential concepts and repetitive trends regarding the combination of big data, analytics, and AI in the field of engineering. Open coding was used to divide the relevant information into categories, after which the open codes were divided into larger topics.

The themes represent how digital technologies can be used in the first place to achieve sustainable engineering practices. The thematic approach can be used to develop a subtle point of view concerning the associations that exist between technological innovation and sustainability results (Nowell et al., 2017).

Reliability and Validity

Several measures were taken to ensure the reliability and validity of the study. First, the selection bias was reduced because several databases were used, and the literature review was more comprehensive (Mongeon & Paul-Hus, 2016). Second, cross-verification of the findings was done by comparing the results of various studies so that there would be consistency and accuracy. Third, an unbiased coding procedure was upheld during the analysis, and clear topics and categories were documented. This increases the validity and replicability of the study (Lincoln & Guba, 1985). Also, the employment of qualitative research techniques and methodology provides a significant degree of rigour to the study.

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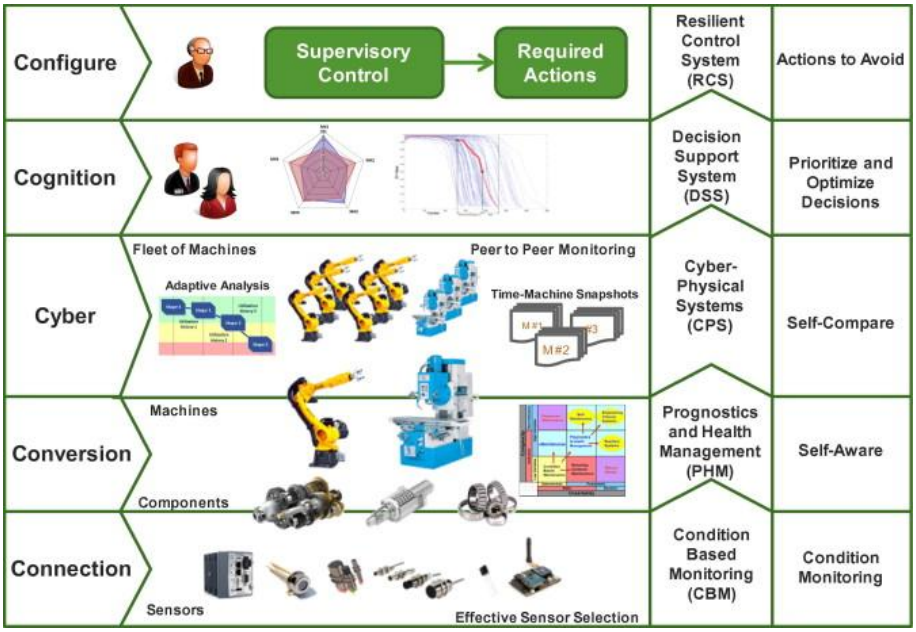


Figure 1: Integration of Big Data, AI, and IoT in modern engineering systems (Industry 4.0)

RESULTS AND DISCUSSION

The thematic review of the studies in the chosen peer-reviewed materials identified five major themes that show how big data, analytics, and artificial intelligence (AI) can be applied to sustainable engineering solutions.

Theme 1: Data-Driven Efficiency in Engineering Systems

According to the results, data-driven techniques yield a great rise in effectiveness in the field of engineering systems. Big data analytics allows keeping an eye on the process of industrial production and distributing it to optimise the process, especially in a smart manufacturing set-up that follows the principles of Industry 4.0 (Wang et al., 2016; Lee et al., 2018). The combination of AI and big data will enable systems to continually analyse production data to optimise production processes to achieve higher operational efficiency and consume fewer resources (Rani et al., 2026).

IoT sensors and machine learning algorithms are used in smart manufacturing systems to track the performance of the system and provide a real-time response to changes. The result is increased productivity, less energy usage, and less waste (Xu et al., 2018). Moreover, cyber-physical systems provide the possibility of a one-way feedback loop and make procedures self-optimised and more sustainable (Boldosova, 2019).

Empirical research indicates that data-driven optimisation can be used to cut operational inefficiencies by a significant factor and help in achieving the sustainability objectives by promoting resource use and decreasing emissions (Zhang et al., 2018). These results underscore the transformational aspect of big data in enhancing efficiency in engineering systems.

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Table 1: Data-Driven Efficiency in Engineering Systems

Study	Application	Key Findings	Sustainability Outcome
Wang et al. (2016).	Smart manufacturing	Data-driven systems improve production efficiency	Reduced resource waste
Lee et al. (2018).	Industrial AI	Real-time analytics enhances operations	Lower energy consumption
Rani et al. (2026).	Industry 4.0	AI optimizes workflows	Sustainable production

Theme 2: Predictive Analytics and Maintenance

Another important use of artificial intelligence in the engineering system is predictive analytics. Through machine learning algorithms, data (both past and present) is used to infer equipment failures so that proactive maintenance plans can be implemented (Lee et al., 2018). Such predictive maintenance systems have a great level of improvement in terms of downtimes, maintenance expenses, and wastage of resources.

Research has shown that predictive models are known to effectively detect possible failures, enhancing reliability and increasing the duration of equipment life (Apata et al., 2026). Predictive maintenance based on AI helps improve the performance of any energy system under consideration and avoids unforeseen failures, which subsequently results in an increase in efficiency and sustainability of the system (Dumlao & Ishihara, 2020).

Moreover, data that can be collected using IoT-enabled systems includes real-time data, including temperature, vibration, and pressure, to identify anomalies. This allows taking action early and minimising operational upheaval (Hector & Panjanathan, 2024). Predictive analytics also helps minimise material waste and unnecessary maintenance operations, supporting sustainable engineering operations (Ojuekaiye, 2025). On the whole, predictive analytics allows for improving the reliability of the system and reducing the impact on the environment through the effective use of resources and decreased downtime.

Table 2: Predictive Analytics and Maintenance

Study	Application	Key Findings	Sustainability Outcome
Apata et al. (2026).	Renewable energy	AI predicts system failures	Increased efficiency
Lee et al. (2018).	Industrial systems	Predictive maintenance reduces downtime	Reduced waste
Ojuekaiye (2025).	Energy infrastructure	AI improves reliability	Extended lifespan

Theme 3: Sustainable Resource Management

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The results of this study show that the use of big data and artificial intelligence (AI) can be important in optimising how an engineer manages a resource or system. Data-driven approaches provide a way to efficiently utilise energy, water and materials through identifying areas where resources are being wasted and optimising the distribution of available resources (Adewumi et al., 2023). Predictive analytics may be used to predict energy demands and thus optimise energy supplies as part of smart grid applications, thereby promoting greater efficiency in energy production and utilisation as well as promoting adoption of renewable energy sources (Zhang et al., 2018). Machine learning algorithms can be adapted to adjust and minimise wastefulness of energy consumption patterns, resulting in enhanced overall system performance (Adewumi et al., 2023).

The AI-based systems also help in water and material resource management. They track the path of resources and optimise their consumption in favour of the circular economy and decreasing environmental impact (Geissdoerfer et al., 2017). Moreover, the optimisation methods based on artificial intelligence make the supply chain more efficient and sustainable with regard to the work with materials and the reduction of waste (Bibi & Yang, 2025). These results reveal the essence of the digital technologies' relevance in sustainable resource management and in advancing the efficiency of all engineering systems.

Table 3: Sustainable Resource Management

Study	Application	Key Findings	Sustainability Outcome
Adewumi et al. (2023).	Energy systems	AI optimises energy consumption	Reduced energy waste
Zhang et al. (2018).	Smart grids	Predictive analytics improves efficiency	Sustainable energy use
Geissdoerfer et al. (2017).	Circular economy	Data tracks resource use	Reduced material waste

Theme 4: Smart Infrastructure and Cities

Smart cities and infrastructure represent one area that heavily employs big data, analytics, and artificial intelligence to assist with sustainable development. In urban environments, the IoT has enabled monitoring of live data so as to effectively manage transportation, energy, and water systems (Bibri & Krogstie, 2017).

The AI-based intelligent transportation system in smart city applications allows for optimal traffic flow, reduces congestion and decreases emissions. Traffic data is processed by machine learning engines; thus, traffic light adjustments can be made on a continuous basis to improve traffic flow and ultimately result in reduced fuel consumption (Vinuesa et al., 2020).

Also, big data analytics can be used in urban planning and infrastructure management to detect inefficiency and anticipate future needs. These systems increase resilience by enabling proactive responses to environmental and infrastructural challenges. Implementing AI and big

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data in smart cities supports sustainable urban development by making it more efficient, less environmentally taxing, and more livable.

Table 4: Smart Infrastructure and Cities

Study	Application	Key Findings	Sustainability Outcome
Bibri & Krogstie (2017).	Smart cities	IoT improves urban efficiency	Sustainable cities
Vinuesa et al. (2020).	Transportation	AI reduces emissions	Cleaner environment
Zemmouchi-Ghomari (2025).	Traffic systems	AI optimises traffic flow	Reduced congestion

Theme 5: Environmental Impact Reduction

The last theme is the role played by big data and AI in mitigating the environmental impact. The systems based on AI allow monitoring and controlling carbon emissions of industrial processes and supply chains accurately (Vinuesa et al., 2020).

Data-driven tools measure carbon footprints and optimise energy consumption, which can lower greenhouse gas emissions (International Energy Agency, 2021). Smart energy systems will apply real-time information to optimise processes and reduce energy wastage to enhance sustainability performance (Zhang et al., 2026).

Climate modelling is also used, and AI processes massive data sets to support climate change predictions and assess environmental threats (Bibi & Yang, 2025). These models help inform decisions and shape policies to control climate change. Further, AI is applied in environmental monitoring disciplines, such as biodiversity and water management, which also contributes to sustainability (Geissdoerfer et al., 2017).

Table 5: Environmental Impact Reduction

Study	Application	Key Findings	Sustainability Outcome
Vinuesa et al. (2020).	Sustainability systems	AI reduces emissions	Climate mitigation
International Energy Agency (2021).	Energy systems	Data optimises energy use	Lower carbon footprint
Zhang et al. (2026).	Environmental systems	AI improves monitoring	Sustainable operations

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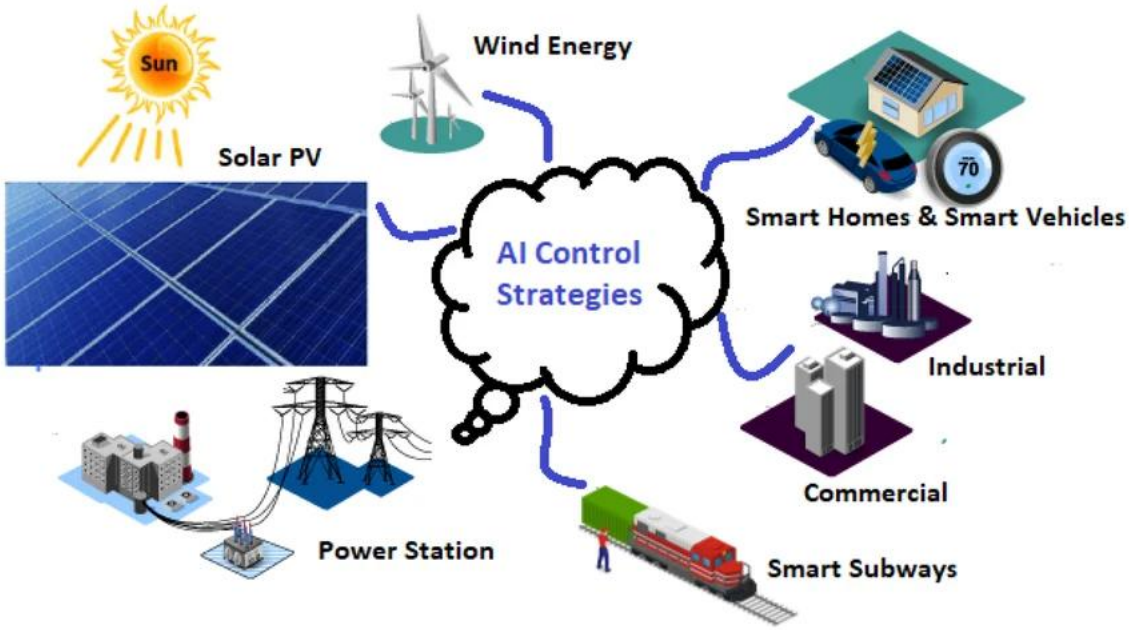


Figure 2: Applications of AI and predictive analytics in sustainable engineering and smart infrastructure

Discussion

Interpretation of Findings

The developed outcomes confirmed that the interplay of big data, analytics, and artificial intelligence (AI) has a considerable positive impact on the sustainability of engineering systems. In all the identified themes, these technologies help improve efficiency levels, better use of resources, and minimise environmental impacts. As an example, data-driven efficiency and predictive maintenance eliminate waste and energy use, and smart infrastructure and environmental control allow designing systems in a more sustainable way and running them (Vinuesa et al., 2020; Zhang et al., 2026).

The results are rather consistent with the systems theory that focuses on interconnections of the parts in intricate systems and the significance of optimisation as a whole (Meadows, 2008). With big data and AI, engineering systems can be made into adaptive and self-regulating systems that will respond continuously to changes in the environment and even to their own functioning. In addition, the findings confirm the theory of digital transformation that implies that innovation, efficiency, and competitiveness within contemporary industries are motivated by the adoption of advanced technologies (Vial, 2019).

The idea of sustainability engineering (balancing economic performance, the environment, and social reasons) can be seen in the integration of these technologies as well (Dincer & Rosen, 2017). The capacity of AI and analytics to give real-time understanding and predictive patterns has helped engineers come up with more efficient but environmentally accountable systems.

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A detailed comparison of the results obtained with the analysed literature allows not only to confirm, but also to clarify a number of scientific propositions. First, the revealed ability of data-driven systems to significantly increase production efficiency and reduce energy consumption is fully consistent with the conclusions of Wang et al. (2016) and Lee et al. (2018) regarding "smart manufacturing", however, this study clarifies that such an effect is achieved only if predictive analytics are integrated with cyber-physical systems, and not due to the isolated implementation of individual digital tools.

Second, the results confirm the thesis of Vinuesa et al. (2020) about the potential of AI in mitigating climate change, but at the same time refute the simplistic notion that the mere presence of algorithms automatically reduces emissions: targeted tuning of systems to carbon footprint indicators is necessary. Third, the established role of predictive analytics in optimising maintenance is consistent with the work of Apata et al. (2026) and Ojuekaiye (2025), but the qualitative evidence suggests that in real-world settings, the lack of standardised protocols for data exchange between IoT devices often limits the scalability of such solutions, which has not been fully reflected in previous studies. Thus, the results obtained both reinforce key points of previous work and outline specific conditions under which digital technologies become an effective tool for sustainability.

Comparison with Previous Studies

The findings of the current study can be compared to those of earlier researchers who report the importance of AI and big data in the process of improving sustainability. As an example, in the study by Vinuesa et al. (2020), AI has great potential for facilitating the attainment of sustainability objectives, especially in energy efficiency, as well as in the mitigation of climate challenges. Similarly, Boldosova (2019) points out that big data analytics are instrumental in improving decision quality and operational efficiency in engineering systems.

Nevertheless, the paper is an expansion of the literature by offering a qualitative synthesis of the integration of these technologies in various fields of engineering practice. Although other studies tend to be application-specific, e.g., a smart grid or predictive maintenance, the proposed research demonstrates the interrelation of these technologies and their mutual influence on sustainability (Zhang et al., 2018).

Also, the results indicate that the paradigm of engineering moves beyond the traditional ways of utilising a particular engineering methodology: the company's inflexible models and reactive decision-making process towards dynamic and forward-thinking systems that can optimise in real-time (Lee et al., 2018). The development is a great break and change in traditional ways, which reflects the transformative nature of the use of digital technologies in engineering.

This research study has various implications for the engineering profession, policymakers, and industry players. To the engineers, big data, analytics, and AI would open up other possibilities of developing intelligent and sustainable systems. These technologies can also help engineers build smart infrastructure, manage resources efficiently, and streamline the work of the system

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(Xu et al., 2018). The use of such digital tools as predictive analytics and machine learning allows for making decisions proactively and enhances the reliability of systems.

The findings would teach policymakers to come up with strategies that can help in the process of sustainable innovation. Regulatory frameworks, funding policies, and public–private collaborations can be used to facilitate the implementation of AI and big data technology by governments (OECD, 2019). The process can be expedited by implementing policies that promote information sharing and technological advances to transform the system towards a sustainable engineering system.

In the case of industries, the adoption of such technologies provides immense value in terms of cost and efficiency in using them. Data optimisation minimises waste, saves on energy, and increases productivity, resulting in better financial performance and sustainability (Wang et al., 2016). These advantages show that the use of digital technologies in conjunction with engineering is economically viable.

Despite these advantages, the literature points to several challenges associated with implementing big data, analytics, and AI. Data privacy and security are one of the main concerns. The growing adoption of data-based systems raises concerns about data protection, cybersecurity, and the responsible use of data (Kitchin, 2013). Protecting information is critical to ensuring engineering system trust and reliability. The high implementation cost is another major problem. Using AI and big data technologies requires significant financial investment in infrastructure, software, and human resources, which could limit their use (Zemmouchi-Ghomari, 2025; Adewumi et al., 2023).

The results of this paper also underscore a number of emerging trends that will dictate the future of the engineering field. The creation of autonomous systems is one such trend: AI-based technologies allow systems to be autonomous with minimal human input (Bughin et al., 2018; Jordan & Mitchell, 2015). Such systems can enhance efficiency and minimise human error in engineering practice.

Another current trend is the notion of Green AI, which aims to create energy-efficient AI models with the lowest environmental emissions (Schwartz et al., 2020). With the increased use of AI, it will be necessary to make AI sustainable.

Lastly, the application of digital twins, which are virtual versions of the real engineering system, is an important development in the engineering field. Digital twins enable real-time monitoring, simulation, and optimisation, making them a valuable source of information to enhance performance and sustainability (Yanginlar, 2026; Atalay et al., 2022). These technologies will play a significant role in the future of sustainable engineering.

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CONCLUSION

This paper examined how big data, analytics, and artificial intelligence can be incorporated to develop sustainable engineering solutions. The results indicate that these technologies are essential for improving efficiency, maximising resource use, and minimising environmental impacts across engineering fields.

The study shows that integrated digital technologies can create intelligent, dynamic systems that respond to complex sustainability challenges. By integrating factual knowledge with improved analysis and computational services, engineering systems can perform better while causing minimal impact on the environment and resources.

The research can advance sustainable engineering overall by providing thorough insight into applying big data, analytics, and AI to enhance innovation and sustainability. It also highlights the importance of interdisciplinary solutions to global issues such as climate change and resource shortages.

Future studies should focus on designing holistic frameworks that integrate these technologies with sustainability concepts, while also addressing data security, cost, and skills development. The practical significance of the study is that it offers engineering practitioners, policymakers and industrial managers a systematic evidence base for implementing integrated digital solutions. In particular, the combination of big data, predictive analytics, and AI enables a shift from reactive to proactive service, reducing operational costs and increasing energy efficiency, which can be directly applied in smart grids, manufacturing systems, and transport infrastructure.

The social impacts include improved urban environment quality through reduced pollution and congestion, increased energy security, and the creation of new jobs in data analysis and intelligent systems maintenance, contributing to a just transition to a digital economy. In addition, the wider use of intelligent environmental monitoring systems enhances industry's accountability to society.

The contribution to scientific knowledge is a high-quality thematic synthesis that, for the first time, brings together disparate examples of big data, analytics, and AI applications in engineering into five cross-cutting themes that demonstrate their collective impact on sustainable development. This creates a conceptual foundation for further development of holistic models of "digital sustainable engineering" that have been lacking in the literature, and paves the way for interdisciplinary research at the intersection of computer science, engineering, and environmental management.

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