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Analysis of innovative technologies in modern engineering: Prospects and challenges

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Abstract

This review represents a comprehensive analysis of innovative technologies in modern engineering. The primary focus was directed towards digital engineering, artificial intelligence (AI) in engineering systems, and innovative materials. The main points addressed are their functional principles, applications, advantages and limitations, and implementation challenges. In particular, Computer-Aided Design (CAD), Building Information Modelling (BIM), Digital Twins (DT), Co-Evolutionary Digital Twins (CoEDT), and their integration with AI-based methods are discussed. This review also addresses research gaps and provides insights into future trends toward resilient, eco-friendly, and efficient engineering practices.

Keywords: Digital engineering, Artificial intelligence, Building Information Modelling, Computer-aided design, Neural networks, Digital twins

1. Introduction

Innovative technologies are problem-solving approaches introduced into existing engineering processes to improve performance, products, or services through new ideas, methods, or materials. They go beyond incremental upgrades and often change how industries operate. The escalating requirements for efficiency, sustainability, and adaptability in engineering, while facing global challenges such as scarce resources and climate change [1], have driven researchers worldwide to develop new approaches and integrate new ideas into engineering.

In general, innovative technologies typically introduce novelty (new materials, concepts, or methods), improve performance (mainly efficiency, accuracy, sustainability, and processing speed), and enable new applications that were previously impractical or impossible [2]. As a consequence, they modify existing practices or create entirely new markets. They are shaping modern engineering, such as additive manufacturing [3], innovative materials [4], and renewable energy systems [5].

Digital engineering comprises model-based systems that integrate diverse data from various inputs, performing modeling and simulations of system behavior to predict overall performance, costs, and issues. The core simulation and analysis tools that have been extensively used in particle engineering for decades are Computational Fluid Dynamics (CFD) and Finite Element Analysis (FEA) [6].

These are considered conventional digital technologies. Novel digital technologies include Digital Twins (DT), artificial intelligence (AI), and machine/deep learning (ML/DL), cloud computing (CC), and augmented/virtual reality (AR/VR). In engineering, CAD [7], Building Information Modeling (BIM) [8], various simulation software, and Geographic Information Systems (GIS) are all emerging digital technologies applied across several engineering disciplines.

Nevertheless, existing research in digital engineering often treats isolated cases and applications, with limited critical analysis of interdisciplinary engineering fields. This gap hinders a comprehensive understanding of how these innovative technologies impact industry and modern engineering. Thus, the impetus of this review will be first to introduce novel and recent engineering methods, starting with their principles, classifications, and applications. Digital engineering methods, AI in engineering systems, and their implementations within digital frameworks; how these novel methods are applied across different fields of engineering, how they're interconnected and complement each other, and their impact on other innovative technologies such as smart materials. Driven by the emergence of Industry 4.0 paradigms and increasing requirements for sustainable systems in engineering, recent scientific literature shows a growing research interest in innovative engineering technologies. Industry 4.0 is based on data and digitalization, cyber-physical systems (CPS), and digital twins (DTs). It aims to transform real physical systems into a virtual environment that could be modeled and simulated [8].

1.1. A literature overview of digital engineering

Digital engineering, sometimes referred to as digital infrastructure, uses technology to optimize project delivery. The optimization process goes from initial surveying and design to construction and long-term asset management. To ensure efficiency, decision-making, and sustainability, digital engineering merges conventional engineering principles with modern digital tools. Digital tools and frameworks such as CAD [7], BIM [8], and related technologies can be integrated or enhanced using AI/DL methods. The resulting models enable simulation and analysis to select the best design option and evaluate potential risk and challenges to optimize project performance (Figure 1).

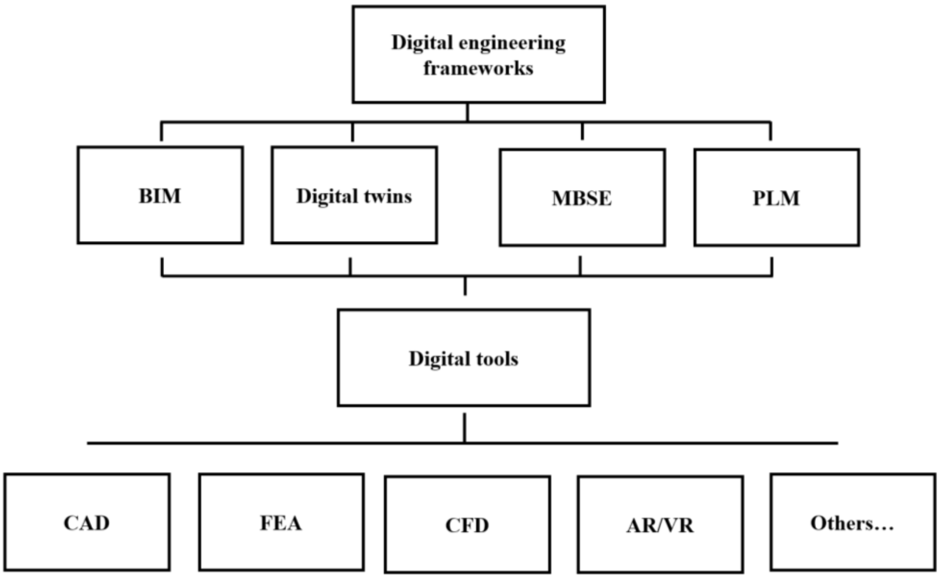


Figure 1. Main digital engineering frameworks and digital tools

In digital engineering, it's essential to distinguish between frameworks and tools. Figure 1 shows their main classification. In addition to the classification in Figure 1, which distinguishes between frameworks and tools, digital engineering can also be broadly classified by modeling approach into two categories: model-Based Approaches (MBAs) and Data-Driven Approaches (DDAs). The latter is used to capture system behavior directly from data. Even though they are highly predictable, they often lack physical interpretability and robustness. These complementary strengths and limitations have motivated the development of hybrid paradigms, such as data-model fusion [10].

1.2. A literature overview of AI tools in engineering systems

Artificial intelligence is the technology that enables computers and machines to learn, make decisions, and solve problems. By relying on pattern-recognition algorithms, the AI can also improve over time. In this vast field, we will discuss what comes next on the most used and recent technologies/models, specifically in engineering.

A field of AI that involves programming a machine to learn to perform tasks by studying examples is called Machine Learning (ML). In engineering, using estimated data from arXiv, the number of published papers related to AI/ML (where ML is used as a keyword) exceeded 60,000 in 2025, up from 29,000 in 2020. It shows the scientific community's strong interest in this technique across disciplines. From a mathematical perspective, ML is developing a model using an optimization algorithm to minimize the errors between the model and our data, in a simple function where $F(x) = ax + b$, fitting a and b until minimizing the distance between the model (function) and points. In ML, several models are used; for example, the one we showed earlier is called a linear model. Other models, such as decision trees and support vector machines, each have their own optimization algorithm. Gradient descent, algorithm CART, and maximum margin are the optimization algorithms for linear decision trees and support vector machines, respectively, as illustrated in Figure 2.

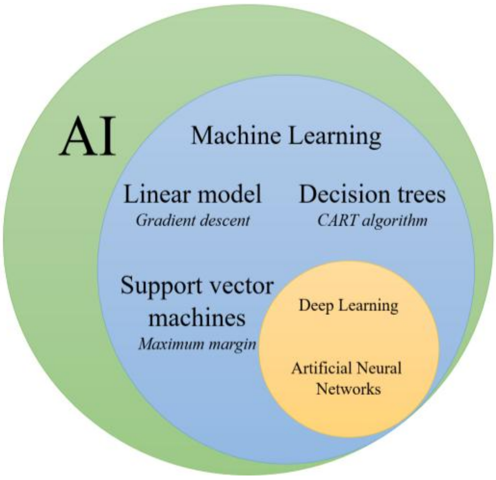


Figure 2. Relationship between artificial intelligence (AI), machine learning (ML), and deep learning (DL), showing standard algorithms used in each category

Another field of AI is Deep Learning, a more sophisticated form of machine learning. Its principle remains the same as ML (provide the machine with data, and the machine will use an optimization algorithm to adjust the data and the model). Yet, the main difference in DL is the number of functions: it does not use a single function, but rather a network of interconnected functions. The principle of deep learning can be summarized as follows: the deeper the network is (i.e., the more functions it contains), the more the machine can learn and perform tasks. For example: recognizing pictures, identifying a person, autonomous driving, etc. That is the reason why it is called “deep” learning. Figure 2 shows a simple representation of the interconnection between AI, ML, and DL. Now, the most critical question is how these networks are built. Inspired by the work of Warren MC Culloh and Walter Pitts in 1943 [11], the concept of artificial neural networks was invented. It was inspired by biology, where excitable cells in our brains (neurons) process and transmit information through our nervous systems. A recapitulation of its functional system is the gateway to neurons: the neuron receives signals at the gateway to neurons (Synapse), where they can be excitatory or inhibitory. In mathematics, it can be positive or negative; if the sum of these signals exceeds a certain threshold, the neuron is activated and produces an electrical signal.

From this biological perspective, a neuron can be considered the transfer function, taking input X signals and producing output Y, where the aggregation is the sum of all signals coming to this function. And synaptic activity is represented by a coefficient that is multiplied by the incoming signal; by matching to biological neurons, the coefficients determine whether the signal is inhibitory or excitatory [12].

Hence, by connecting several of these functions, as in the neurons of the human brain, it would be possible to solve any logic problem. The main drawback is that synaptic activity could not be determined; with the development of learning algorithms, it became possible to define synaptic activity, and Artificial Neural Networks have seen the light. In simple terms, ANNs are a set of AI algorithms inspired by the functioning of biological neurons; they can learn and perform complex tasks.

1.3. A literature overview of innovative materials in modern engineering

Innovative materials can be defined as materials that respond to external stimuli, such as self-healing materials, piezoelectric materials, or shape memory alloys [13]. They enable adaptation and response to external variations. They can modify their physical properties, such as shape, color, or conductivity, when subjected to changes in temperature, humidity, moisture, or light [4]. Piezoelectricity in quartz crystals, where the mechanical stress on quartz produces an electrical voltage, and applying a voltage causes the crystal to deform [14]. This fundamental link between material structure and external stimuli underpins much of today's innovative materials research. After being mechanically deformed, shape-memory alloys can regain their original shape in response to heat or electrical stimulation. At the same time, self-healing materials can autonomously repair damage [4].

The following subsections review the literature for each technology individually: digital engineering, AI-enhanced technologies in engineering systems, and innovative materials. While highlighting the research that interconnects these three areas of innovative technologies, it also prioritizes the most recent research topics.

2. Research method

This review comprehensively analyzes innovative technologies in modern engineering, focusing on the intersection of digital engineering, artificial intelligence in engineering systems, and innovative materials, and their role towards sustainable engineering technologies.

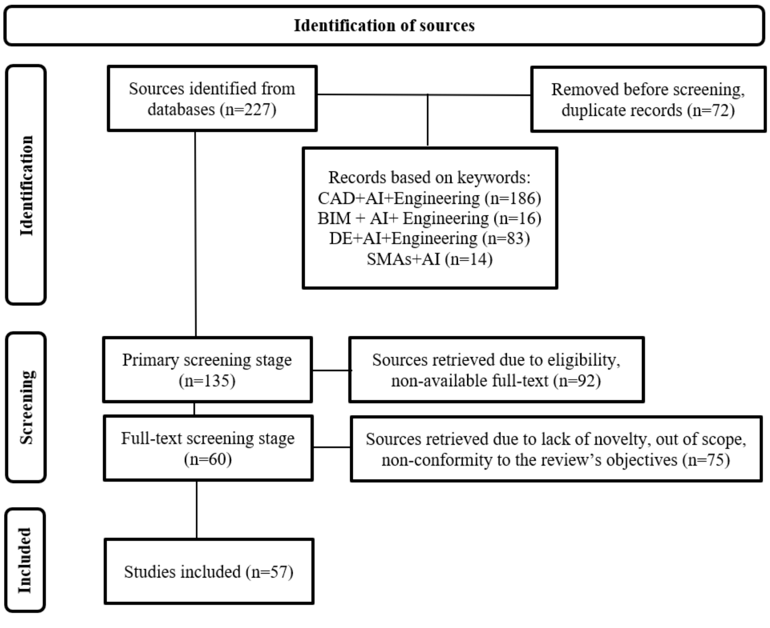


Figure 3. PRISMA flowchart

In this study, we have focused on recent global trends in scientific publications from 2024 to 2025. Literature selection was conducted through scientific databases such as Web of Science, Scopus, and IEEE Xplore. Keywords related to each technology domain were used. For digital engineering: FEA, FEM, CAD, CAE, BIM, Digital Twins, PLM, and MBSE, each keyword was combined with a keyword related to "engineering" or a specific engineering domain, such as mechanical engineering, materials science, electrical engineering, and civil engineering. In AI, focus has been given to broader-defining keywords: ML, DL, and ANN. In innovative materials, the focus has been on integrating AI methods only into shape memory alloys and crack-healing materials.

The inclusion criteria were: 1) choosing only peer-reviewed journal articles, 2) high-impact and relevant reviews, 3) written in English, and 4) published papers within the last two years (2024-2025). The exclusion criteria were based on the following: if the research is related to a specific technology without emphasis on sustainable structures, or outside the engineering context (Figure 3). Suppose it represents a fundamental concept purely related to computer science. Or if the papers proposed a methodology lacking innovation, or if the core research idea was replicated without a conceptual advancement.

According to the PRISMA flowchart, the initial 268 papers were identified. The preliminary screening phase was done based on the abstract, key figures, and conclusions. The selected papers underwent a full-text screening. A comprehensive analysis was conducted across technologies to identify relative advantages, limitations, and research gaps.

3. Results and discussion

3.1. Results on innovative approaches in digital engineering

In manufacturing, product development, and prototyping, we find CAD to be the most widely used digital technology. CAD, in simplest terms, is the use of a computer for technical drawings, either in 2D or 3D, used in different fields of engineering. Popular software includes SOLIDWORKS, AUTOCAD, CATIA, and Fusion 360 [15]. Regarding the impact of CAD on optimization procedures, Enahoro and Ekiugbo [16] conducted a systematic review of the evolution of CAD in mechanical engineering. The study has shown the global influence of CAD on optimization procedures and educational practices. They showed that modern CAD systems have evolved into comprehensive platforms integrating complementary tools such as Computer-Aided Engineering (CAE), FEA, CFD, and Computer-Aided Manufacturing (CAM). The main advantage of these platforms is their enhanced efficiency and iterative design workflows. However, the significant limitations were insufficient infrastructure and well-trained personnel, and, most importantly, security concerns that hindered its broader adoption.

CAD isn't a tool used exclusively for geometric design; Klimchik et al. [17] used it to identify elastic-static parameters of robotic manipulators. They concluded that virtual CAD experiments can, in fact, replace physical testing [18]; hence, saving time and resources. Their work was an early example showing that CAD is not only a tool for visual design but also a platform for simulation and mechanical analysis. Recently, Gao et al. [19] combined CAD/CAM software (Pro/ENGINEER) with advanced machining simulation tools (VERICUT) to analyze the machining process of a two-cylinder engine component. In brief, CAD can be used to predict tool motion, thereby enhancing manufacturing efficiency in complex tool machining.

Moreover, Parnell et al. [20] have proposed a Decision Analysis Data Model (DADM) to support decision management inside a digital engineering environment. Their approach was to follow DAMA's data management instructions, which begin by defining how data should be structured through data models. Firstly, it should start with a conceptual data model; this one describes concepts at high decision levels in the simplest way to make it easy for managers to understand. The following data should be a logical data model that defines specific data elements and their relationships. The authors have developed DADN using model-based systems engineering (MBSE) software, following the international standards such as ISO/IEC/IEE 155288, the INCOSE Systems Engineering Handbook, and data management frameworks. Their model was successful in mapping decision-making processes, identifying structures, characterizing them, and evaluating them. By implementing decision management processes and data definitions within an MBSE context, the model improved traceability and consistency.

Other technologies, such as BIM and GIS, are widely applied in infrastructure and construction. BIM is a digital tool for engineering design, construction, and management. Its role is to ensure that building data is shared and transferred in real time among all contributors to the project. Figure 4 shows the main advantages of BIM technology and explains the different processes involved when visualizing building information. It starts with data collection, such as technical specifications and drawings. Based on the collected data, a three-dimensional building model is created using BIM software. The components are built within this BIM environment and modeled with accurate geometry, including their spatial positions, to match real construction conditions. We must note that parameters such as material properties, cost, and quantities are all included. Then, BIM will provide a real-time visual presentation throughout the entire project lifecycle [21].

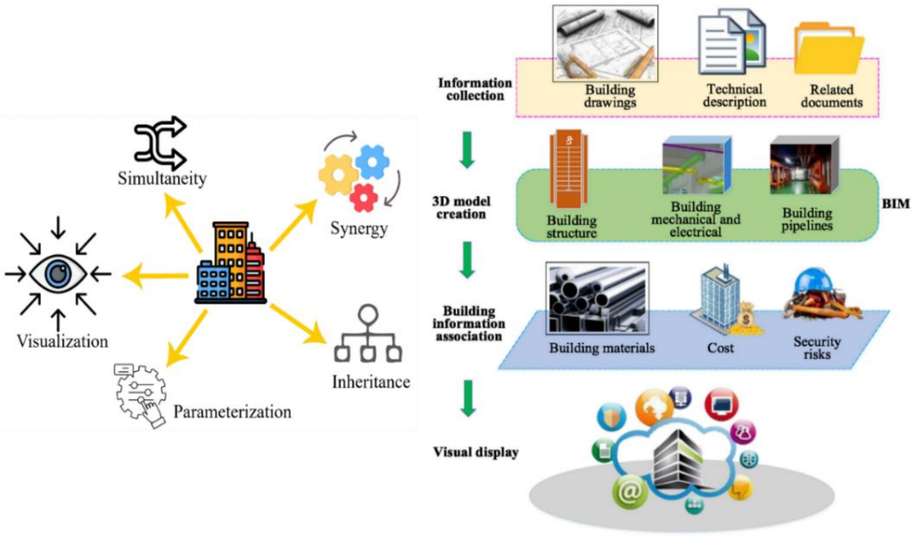


Figure 4. Illustration of key advantages of Building Information Modeling technology

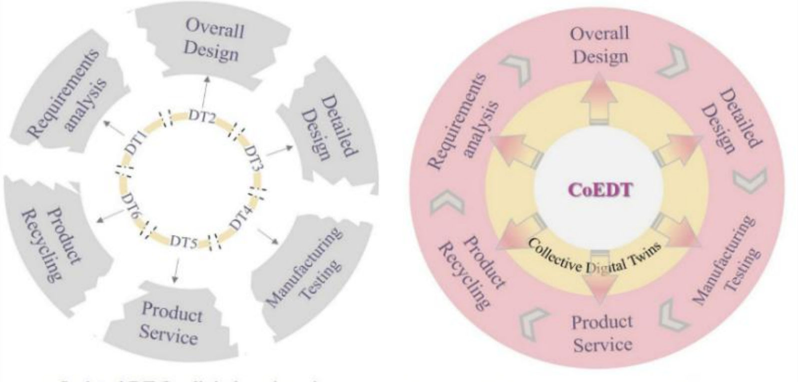
Within the same field of construction and infrastructure, Geographic Information Systems (GIS) is found to be an indispensable digital tool, comparable to GPS (Geographic Positioning System). The main concerns of GIS technology are positioning, data acquisition, and dissemination [22]. Integrating GIS technology into BIM enables a more precise definition of spatial coordinates within the BIM environment. In the automotive and aerospace industries, FEM/FEA is a widely used tool in aerodynamic and mechanical simulations. It relies on the principle of discretizing a structure into finite elements interconnected by nodes. The equations are solved at the elemental level and then assembled to predict the overall response of the system.

The FEM is suitable for simulating physical phenomena such as stress and heat transfer. It is used to support experimentation or to make reliable performance predictions. Although FEM is a numerical approach implemented within simulation platforms, it is a key digital technology. The previous tool helps analyze mechanical, structural, and thermal behaviors in solid mechanics [23]. In fluids, another numerical simulation method is used, Computational Fluid Dynamics, which uses computational algorithms to predict and analyze fluid behavior. Both FEA and CFD are considered the backbone of digital simulation tools; they are often integrated with CAD, BIM, and digital twins, enabling virtual testing, real-time updates, and are essential to model-based systems engineering MBSE [24], [25].

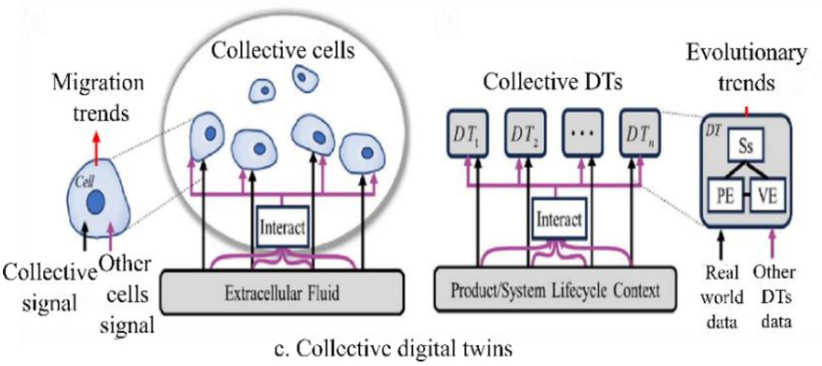
Another growing interest is in other digital tools, like Virtual Reality (VR) and Augmented Reality (AR). The first one, VR, is considered a virtual entity within a simulated environment. It replicates real-world scenarios in which users interact with a virtual environment in a simulated world. Some examples include pilot training, medical training, or construction (walking inside a building before it is built). On the other hand, AR adds digital information to the physical world, making it more interactive. Thus, enhancing the experience and engagement across diverse activities. In engineering, both digital tools are extensively used in automotive and aerospace [26]. Both techniques are appreciated because they provide interactive ways to train, design, and test prototypes without risk or cost. A digital twin is a virtual representation of a physical object, system, or process. It is dynamic and data-driven, and must be represented in real time through synchronization and computational analysis. It combines models from multiple domains, sensor inputs, and machine learning techniques to simulate, predict, and optimize the behavior of its real-world counterpart. The digital twin is broadly made of three main components: 1) a physical asset equipped with sensors, 2) a virtual model, and 3) a bidirectional data link that connects the virtual and the physical system. Digital twins are an emerging technology within Industry 4.0; they provide maintenance practices with real-time monitoring and predictive analysis [27].

Fei Tao et al. [10] introduced data-model fusion (DMF) in their review as a foundational approach for smart manufacturing and digital engineering that overcomes the limitations of conventional modeling paradigms. They clearly demonstrated that neither MBAs nor DDAs were sufficient for addressing the growing demands of modern digital engineering systems. DMF, as a hybrid paradigm that successfully integrates both MBAs and DDAs, has proposed a generic conceptual framework that illustrates the interaction among data, models, and decision-making throughout the product life cycle. Their review demonstrated that DMF can be used across different engineering phases, including product design, manufacturing, maintenance, and final-product testing.

Digital twin technology is not different from using digital models to simulate a physical phenomenon. To define it, we need to compare it to a simple simulation. The difference lies in scale: a simulation studies a single process, whereas a digital twin can run multiple simulations to study various processes. They are designed around a two-way flow of information and benefit from obtaining real-time data. The main issue encountered when multiple digital twins are connected is the lack of effective, real-time data sharing across the entire life cycle (including design, manufacturing, operation, and maintenance). To overcome these limitations, Co-evolutionary Digital Twin (CoEDT) is proposed. Instead of treating digital twins as isolated tools used at a single stage, CoEDT connects all digital twins throughout the product life cycle. It is not simply about sharing information; it is about enabling multiple digital twins to learn from each other and evolve together. Tong et al. [28] introduced the concept of Collective Digital Twins (CollDTs). It was inspired by collective cell migration in biology. Figure 5 illustrates the DT, CoEDT, and CollDT methods.



a. Isolated DT for digital engineering b. Co-evolutionary DTs for digital engineering



c. Collective digital twins

Figure 5. DT, CoEDT, vs CollDT principles

Instead of isolated digital twins, multiple digital twins are connected and interact continuously. Digital twins can evolve together throughout the entire product lifecycle (from design to operation). They achieved this using Model-Based Systems Engineering (MBSE) to link models and data simultaneously. Finally, they used information theory to quantify and analyze how these digital twins influence one another over time. This allows the researchers to quantitatively track how the digital twins change, share information, and evolve together throughout the product's lifecycle. They have shown that CoEDT enables stronger interaction and integration across all life-cycle phases.

They also compared their concept to the Cognitive Digital Twin (CDT) approach. Table 1 shows the main differences between DT, CDT, and CoEDT. CDT is mainly oriented toward industrial outcomes, supporting decision-making and control in manufacturing through artificial intelligence. CoEDT, on the other hand, focuses on system processes and performance, enabling capabilities such as self-organization, self-management, self-optimization, and self-monitoring [28].

Table 1. The main differences between DT, CDT, and CoEDT

Content	**Digital Twin (DT)**	**Collective Digital Twin (CDT)**	**Co-Evolutionary Digital Twin**
Integration of IoT	Have	Have	Have
Integration of the lifecycle	Lack	Have	Have
Continuous evolution	Lack	Have	Have
Core competence	Interaction	Semantic knowledge	Self-collaboration
Scalability and fault tolerance	Lack	Lack	Have
Consistency	Lack	Lack	Have

Digital engineering methods are widely applied across engineering disciplines such as civil, mechanical, and electrical engineering, as well as in optics, the environmental sciences, and defense systems. More specifically, engineering methods support the design of infrastructure such as roads, bridges, levees, wastewater treatment facilities, airports, etc. Voth and Sturtevant [29] studied the application of digital engineering in modern defense marine systems (specifically: Naval Power and Energy Systems). They showed that it is a transformative approach to managing complexity by extending traditional systems engineering through a comprehensive digital framework. In fact, before new ship systems are installed, they must be tested in an environment that closely mirrors real-world ship operations. Importantly, it helps avoid failures and reduces risks once the ship is operational. They showed that adopting a multi-factor digital engineering framework – grounded in established systems engineering principles – can significantly reduce program risk by closing the so-called “digital divide” among design intent, analysis, and implementation.

In physics, Murzin et al. [30] reviewed the application of digital engineering to laser-processing manufacturing. In micromachining and cladding, the integrated DT enabled real-time adaptation of processing parameters. To achieve this, they examined how to combine freeform optics with AI to ensure dynamic adjustments of beam profiles. In another study [31], the same authors examined how digital engineering methods are applied to diffractive optics. They used DE-assisted methods to develop and design better strategies for Diffractive Optical Elements (DOEs). Combining machine learning, geometric algorithms, and numerical modeling enabled accurate laser beam shaping. Consequently, better precision in laser processing applications.

In additive manufacturing, Berdanier et al. [32] applied Navier-Stokes (RANS) and CFD simulations to the additive manufacturing of a high-pressure turbine vane. Their purpose was to investigate how geometric deviations caused by additive manufacturing affect overall aerodynamic performance. They successfully implemented as-built geometric data into their model to predict realistic aerodynamic behavior. Recent advances in digital engineering have shaped mechanical design. Zhang et al. [33] introduced CPS architectures for developing CNC machining tools. Including CAD/CAM integration, it enabled predictive maintenance, process optimization, and adaptive machining methods. Zhuang and Yao [34] applied 3D CAD in automotive machinery. They showed that the design of a conveyor chain for automobile axle forging was optimized using virtual prototyping and dynamic trajectory planning.

All the aforementioned research highlights how integrating digital techniques enhances performance and makes engineering modeling and design less time-consuming. On the other hand, in the context of industrial platforms, Norsahperi et al. [35] applied a hybrid CAD approach that uses both 3D and 2D models to an autonomous Motorized Adjustable Vertical Platform (MAVeP) (used for satellite test facilities [36]). They investigated its dynamic behavior and found that despite the acceleration torque rates, the jerk remains well within ISO standards. Their lifting subsystem required a maximum torque of 631 N.m (no matter what the speed mode is) while the baseplate loading required approximately 14.7 N.m.

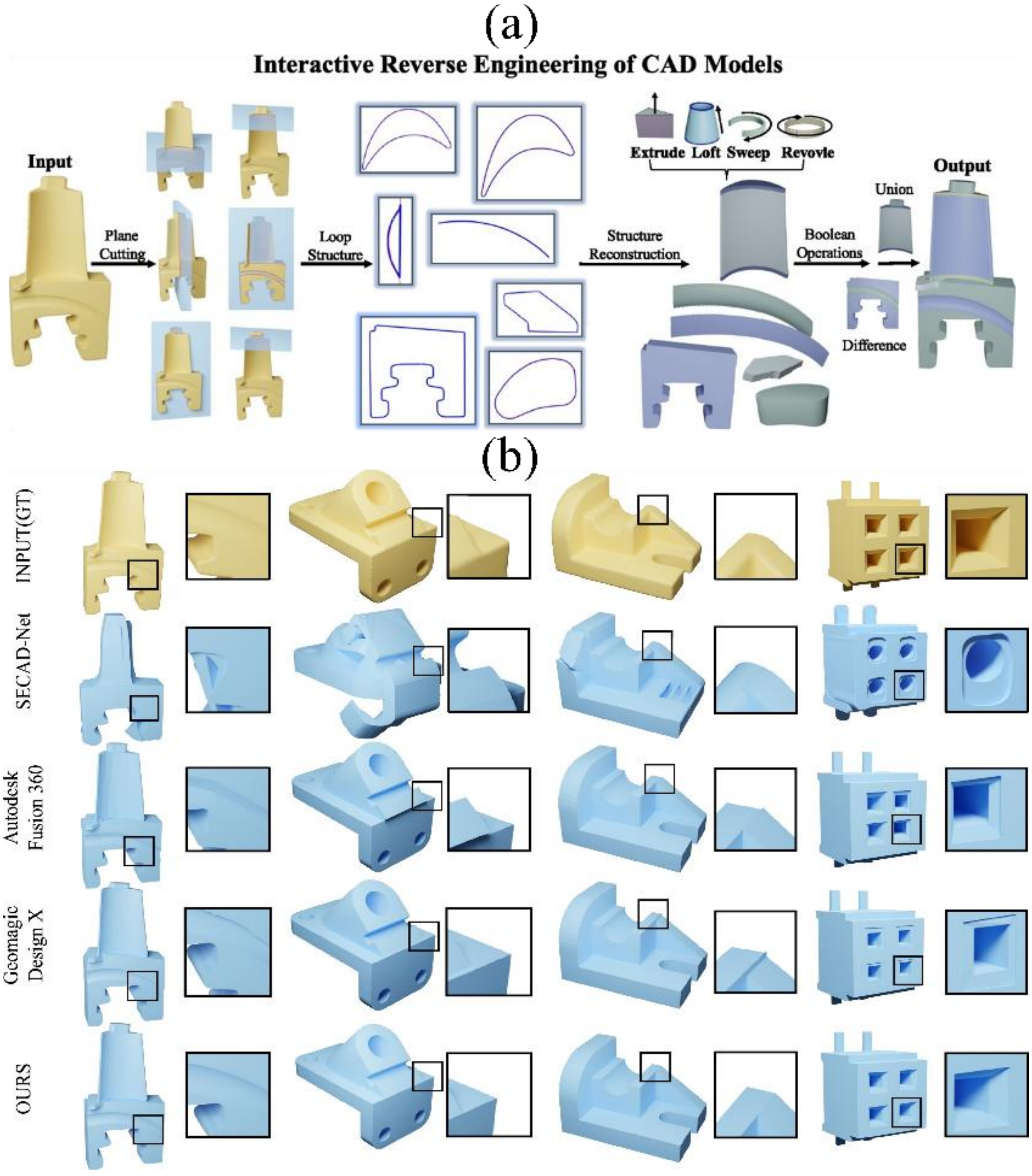


Figure 6. a) Illustration of the initial mesh model cutting process using a plane in the reverse engineering approach for CAD reconstruction, b) comparative results of the proposed CAD reconstruction model against other reverse engineering methods on the Thingi10K dataset, demonstrating superior performance as evaluated by Z. Zhang et al. [39]

The obtained values confirmed that their method accurately predicts the actuators' demands and reduces over-specification. When speaking of CAD's analytical capabilities, several works by Pappalardo and his research team [37], [38] used multibody dynamic modeling in combination with CAD to simulate the motion of quadcopters, aircraft components, and manufacturing processes. Their combined research shows that the broader field of digital engineering encompasses CAD models not only for design representation but also for simulating real-world dynamics.

Reconstruction of CAD models when the original design document is missing is crucial in reverse engineering. Z. Zhang et al. [39] have used an approach consisting firstly of cutting the input mesh model using a plane, as shown in Figure 6a. Then, fitting the cutting line to edges using primitive collected data, the loop structure is made using a series of CAD operations such as extruding, lofting, and sweeping. By integrating Boolean operations, the generated CAD models are assembled to approximate the final geometry. The authors have conducted a series of comparisons with other reverse engineering models, such as the Thingi10K dataset. Figure 6b shows that, among the models, the construction model achieved the best results.

G. Korsovesczki et al. [9] have integrated a new technique called photogrammetry into the realization of the digital twin of a Mitsubishi RV2-AJ MELFA robotic arm. The photogrammetric design consists of reconstructing an object from photographs taken from various angles. Using measurements and calculations, geometric information can be obtained to determine the object's three-dimensional properties. The data were integrated into a software called Meshroom, developed by AliceVision, to construct a three-dimensional model from 2D images. The digital twin helped reconstruct a 3D model, and their proposed method enabled reverse engineering based solely on image reconstructions.

The integration of BIM and robotics is rapidly transforming the construction industry by enabling more intelligent, adaptive, and efficient workflows. BIM provides robots with precise geometric and semantic information for accurate task execution, while robots, in turn, supply real-time as-built data to refine and update BIM models, creating a dynamic feedback loop. Alvur et al. [40] have studied the impact of BIM technology on enhancing the energy efficiency in existing building stock. In their analysis, they integrated standard methodologies (such as Industry Foundation Classes (IFC), Information Delivery Manual (IDM), and Model View Definition (MVD)) with the BIM digital framework.

They emphasized that the main challenge is around data interoperability and the need for standardized workflows, emphasizing that overcoming these barriers is necessary to fully realize BIM's role in sustainable building renovation and performance optimization. Barbosa et al. [41] integrated BIM and Virtual Design and Construction in hydropower plant projects. Despite the highly complex infrastructure, their implementation approach enabled successful coordination and data management.

3.2. Results on artificial intelligence in engineering systems

In recent years, the integration of artificial intelligence has expanded the capabilities of digital engineering by enabling automation and enhancing engineering workflows. The implementation of digital engineering can range from relatively simple applications (such as producing engineering drawings) to more advanced practices, including the development of digital twins to support automated asset operation and maintenance.

Efficient management and retrieval of CAD models is another critical aspect of modern digital engineering.

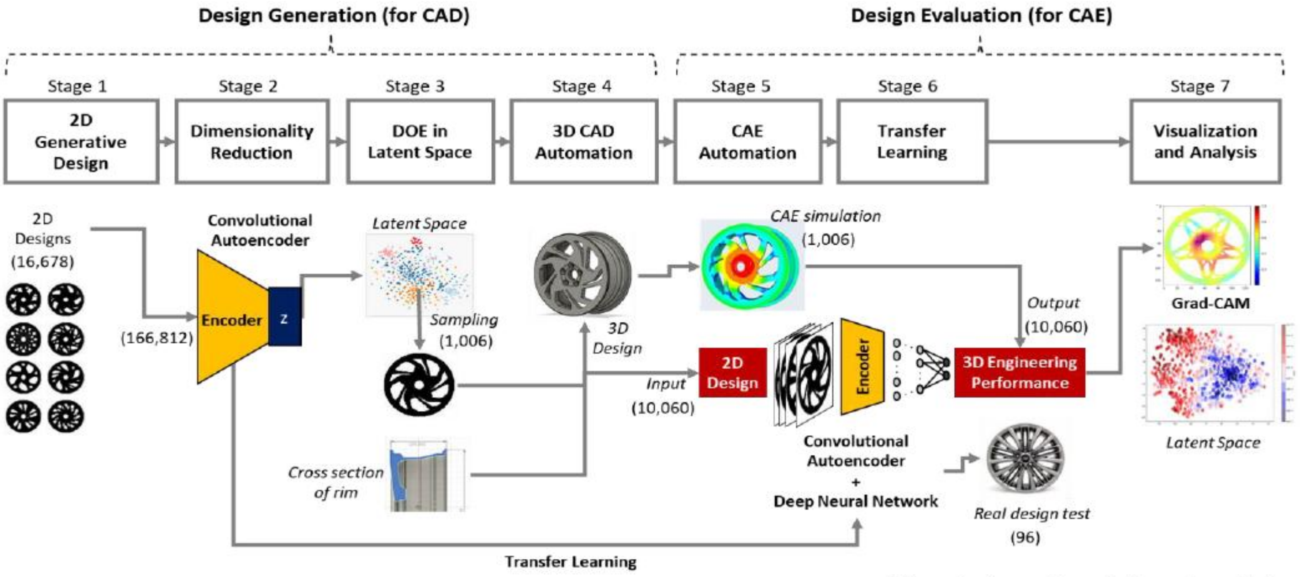
Searching for texts or images in databases is relatively easy. However, searching for 3D models is much harder because they contain complex features. Manda et al. [42] developed CADSketchNet, an annotated dataset designed to facilitate deep-learning-based 3D CAD model retrieval from sketches. They also added hand-drawn sketches of these components, allowing users to draw a sketch and then search for matching 3D models. To do this, the authors tested different deep learning-based search systems. Convolutional Neural Networks (CNNs) were used for image recognition, machine vision [43], comparison, and image search [44]. Meanwhile, hand-drawn images were used as the dataset to train deep learning models.

In architectural design, text-to-image AI using GAI (Generative Artificial Intelligence) has become increasingly popular. Used by architects as an experimental tool, several leading companies released updated versions of AI image generators. In 2022, MidJourney and ARCHITECTURES launched an integrated tool within their software; Adobe Firefly, Hypar, Veras, Monograph, and Snaptrude launched in 2023, 2024, 2025, and 2025, respectively, and others as well [45]. They basically use a deep learning model like DALL-E, developed by OpenAI.

Within the same context of generative artificial intelligence. V. Liu et al. [46] have used an AI-enhanced digital tool (CAD). They integrated the 3DALL-E system into the 3D CAD design workflow. In their study, instead of replacing engineers, they used several professional designers to use their model, aiming to bridge natural language and visual design exploration. They concluded that AI is most effective when used early in the design cycle as a source of ideation rather than as a direct substitute for CAD tools.

In CAD, a series of commands, such as drawing a line or extruding, is used to create a 3D model. However, starting from 3D meshes or point clouds obtained from scanning real objects is complicated and needs extensive manual work by engineers. Yu et al. [47] proposed a framework named GenCAD-3D that learns how CAD and geometric data relate to each other and uses diffusion models to generate and retrieve CAD command sequences, as the automatic generation of CAD programs by deep learning models remains impossible due to the lack of available datasets. The authors have also integrated SynthBal, a tool that generates synthetic CAD data. Their study showed fewer invalid CAD outputs, accurate reconstruction of CAD models in reverse engineering, and improved generation of complex geometries. GenCAD-3D produces CAD programs that are precisely the same as the input, but it can also create slightly different versions instead of copying them.

Another notable development is the integration of deep learning, specifically CNNs, within CAD and CAE environments; Yoo et al. [48] proposed a framework for AI-driven generative design that automates the creation and evaluation of 3D conceptual models. The framework is divided into several stages. Each stage takes the output of the previous one and advances the design process, from simple 2D designs to simulation and prediction. Their framework model is explained in Figure 7. Stage 1 consists of creating several 2D wheel designs, whether they are collected from existing images of commercial wheels or by an AI-based design method [49]. The second step consisted of compressing the images into simpler forms using a neural network tool. Then, the selection of representative designs is turned into a 3D model. Lastly, the models are used for simulations, with a CNN applied in the 6th step to estimate the simulation outcome of a new wheel design without running a complete simulation. At the same time, the last step consists of visualization and analysis of results.



*The value in parentheses is the number of data.

Figure 7. Deep CAE/CAD frameworks

Several other studies [7], [50], [51] have shown the growing role of Generative AI integrated with CAD automation in creating innovative mechanical designs, especially in environments with limited data.

Recent advances where BIM meets AI technologies have significantly enhanced sustainability, decision-making, and operational efficiency in construction and engineering. Qiang et al. [52] integrated IoT technologies and deep learning models (CNN) within the BIM framework. AI integration enabled context-aware automation and high-precision occupant comfort assessment.

Nguyen [8] has focused on the role of VR and AR tools integration within a BIM framework. They showed that the BIM model optimized workflows and provided good risk predictions. The AI integration has promoted sustainability through energy simulation and waste management. Jadshoubi et al. [53] developed an automated BIM quality evaluation system with integrated AI modules. AI tools such as Power BI were primarily used for data extraction, storage, and visualization. The results showed an average quality score of 87.6% and a 30% reduction in failures when applied to a Canadian infrastructure project.

Recently, in agriculture, Han et al. [54] proposed a BIM model for cost prediction using a Grey Backpropagation Neural Network (GBNN) optimized by the Sparrow Search Algorithm (SSA). Yielding a maximum relative error of 2.99%, their model showed that BIM integrated with neural networks significantly improves accuracy and reliability in construction budgeting.

Their modelling framework is shown in Figure 8, where their model could be explained and detailed as follows. The first step is to create a 3D digital model of the water conservancy facility. They include the construction schedule and cost-related information. Collectively, they formed a 5D-BIM model, meaning it integrated a 3D model with time and cost. The BIM model enabled the calculation of real quantities of concrete, steel, and construction volumes.

The AI neural network was then used to predict unit prices, enhanced with the bird behavior method, SSA, which helped the model find a better prediction setting. It must be noted that the AI can learn from past data and accurately predict future prices. This way, the BIM provides information about how much material is needed, while AI answers how much it will cost.

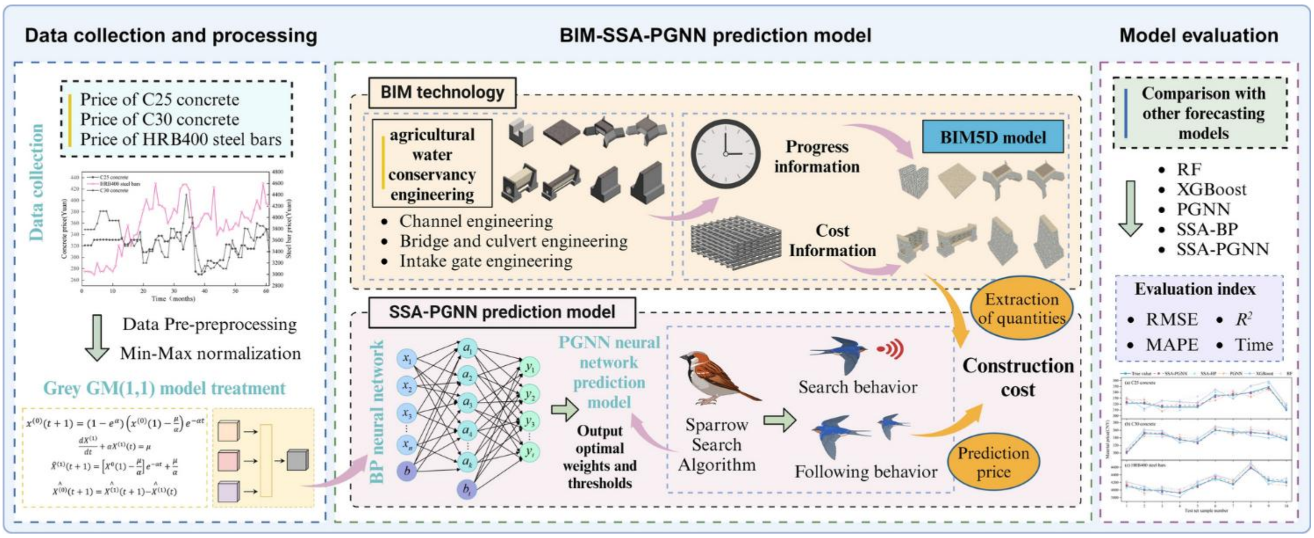


Figure 8. A BIM model is used in the cost prediction of an agricultural water conservancy. The BIM model was used with PGNN and SSA

3.3. The intersection of AI and innovative materials

With the rapid growth of big data technology [55], which increased from 175 Zettabytes in 2021 to 175 Zettabytes in 2025, materials science engineers must be included in the AI industry and its development [56]. In materials science and engineering, AI tools integrate knowledge mined from "Statistical Pattern

Recognition" [57]. However, AI tools do need a deeper analysis and a better understanding of the findings; AI algorithms also need to be tasked with generating an understanding of the obtained results [58], which is a task of human intuition.

In materials science, four paradigms of AI are included: Empirical Interatomic Potential Development, ML-Based potential, Property prediction, and Molecular discoveries using Generative Adversarial Networks (GAN). The ML in Materials Science and Engineering starts by preparing the data, mainly from first-principles calculations, classical molecular dynamics simulations, DFT, or experimental data.

A recent review that combines a digital engineering tool (BIM), AI, and the field of innovative materials has shown how the three technologies can be combined to create more resilient and sustainable structures [59]. The review highlighted the use of shape memory alloys and high-performance fiber-reinforced polymers (FRPs) [60]. Shape memory alloys, in particular, can recover their original configuration after deformation, significantly reducing residual damage after earthquakes. With the aid of the BIM digital framework, the structure's seismic design, simulation, and visualization in response to seismic forces were possible by maintaining real-time interdisciplinary coordination among engineers, architects, and contractors. By integrating machine learning, a large seismic dataset can be used to predict vulnerabilities and optimize structural design. The integration of the three fields has made the design process more innovative, more robust, and sustainable.

Radhamani and Balakrishnan [61] investigated the relationship between electronic factors and phase transformation temperatures (PTT) in NiTiCu shape memory alloys (SMAs). Their study combined theoretical analysis with artificial neural network (ANN) modeling to predict critical phase transformation temperatures. Similarly, Sivaros et al. [62] explored the use of ML methods, including boosted trees, random forests, support vector machines (SVMs), k-nearest neighbors (KNN), and ANN. They used experimental data to train and validate models that capture the strain behavior of nickel-titanium shape memory alloys (NiTi SMAs, or Nitinol). Their results proved that ANNs can accurately predict complex nonlinear SMA behavior, reducing the need for extensive experimental testing and offering a powerful tool for designing SMA-based applications that exploit superelasticity and the shape memory effect. Other researchers have integrated ANN to predict the mechanical behavior of several SMAs [63], [64].

Self-healing materials are materials that can heal cracks, such as MAX phase ceramics. Their oxidation resistance enables them to form multi-layered oxides on their surface. This property enabled them to form those oxides within cracks. It allows them to fill the voids, ensuring a continuity of matter and load transfer. In civil engineering, with the aid of absorbed moisture, some phases can expand and fill cracks created by vibrations or external stresses. Several researchers have used AI tools to predict crack initiation and propagation, as well as healing behavior in self-healing materials.

Recently, Tian et al. [58] explored the potential of AI algorithms to estimate the crack repair rate of self-healing concrete (SHC). They used two evolutionary machine learning methods, Gene Expression Programming (GEP) and Multi-Expression Programming (MEP). They concluded that fibers in the concrete composite are positively associated with healing performance [65]. The aforementioned research works collectively show how AI is reshaping modern engineering technologies, including the field of innovative materials.

3.4. Research gaps, challenges, and future trends

3.4.1. Digital tools and frameworks

Regarding digital tools and frameworks (BIM, CAD, FEA, CFD, DMF), the key gap lies in insufficient exploration of data interoperability challenges when integrating digital tools such as CAD and BIM with emerging formats (e.g., DMF for digital manufacturing). Even though these tools enhance design accuracy, there is a lack of standardized protocols for model conversion and real-time collaboration, especially in multi-disciplinary projects or when data is insufficient or inaccessible. Furthermore, gaps exist in evaluating cybersecurity risks in cloud-based BIM environments and the scalability of digital twins for complex infrastructures. Despite the significant development of CoEDT and the recent CollDT concept, research should focus on validating these architectures on a large-scale industry. Create case studies to explore scalability; research on case studies is scarce.

3.4.2. The intersection of AI and digital frameworks

There is a strong growth in research on integrating AI models (such as IoT) with digital twins to support real-time decision-making and data sharing. However, most works focus on predictive modeling and simulation. Real-time feedback on materials or system behavior should be integrated, especially for systems that evolve or materials whose properties can change under stress or fatigue during processing.

Our coverage of AI tools' integration with CAD/BIM has highlighted a prominent gap: limited empirical validation of these models in real-world engineering scenarios. Ethical considerations, such as data privacy and AI-driven BIM, as well as the energy consumption of DL models in large-scale simulations, should not be taken lightly. Table 2 summarizes the main limitations addressed in the literature. Future research should also focus on explainable AI (XAI) methods integrated into CAD, BIM, and DT platforms. This will be an essential topic for structural design, aerospace, and defense systems.

Table 2. A summary of the identified key innovative approaches in engineering and their limitations

Focus area/Innovative approach	Limitations	Reference
Smart manufacturing and digital engineering/ Hybrid DMF framework applied through different stages of the product lifecycle	Due to the large amount of data processing, fusion accuracy is reduced. Lack of models and data integration across all stages of a product lifecycle. Inability to handle noisy, missing, or inconsistent data to ensure reliable results	[10]
CoEDT in digital engineering/Integration of CoEDT using MBSE for evolutionary data sharing between multiple DT.	Lack of honest data sharing, lack of scalability, and limited validations in large-scale industries	[28]
Integrating CNN into CAD+CAE for generative design/ automating 2D-to-3D design conversion + simulation and prediction	Complexity in handling conceptual design, lack of broad applicability (shown only for specific applications, mainly wheel design)	[48], [66]
Integration of IoT and BIM in laboratory monitoring/ Development of LabMonitor system using a combination of BIM, IoT, and CNN-based models	Data interoperability issues, non-standardized workflows, and a lack of accuracy in dynamic environments	[52]
AI in shape memory alloys/combining theoretical electronic factor analysis with ANN to predict phase transformation in SMAs (innovative materials)	Lack of experimental data and real-world validations	[61]
AI in SMAs/Application of feedforward backpropagation neural networks trained on experimental data to model nonlinear strain behavior in SMAs	SMAs' nonlinear behavior makes data selection and integration challenging, leading to poor model generalization and limited adoption of advanced AI techniques.	[62]

3.4.3. Smart materials and integration of AI in engineering

The significant research gap in this field is that innovative materials are slowly, but in a growing trend, integrating AI technologies; however, AI should benefit from the properties of these materials as sensors for technologies such as digital twins and BIM [67]. Regarding data-driven materials design, the incorporation of

AI-predicted material behavior into MBSE, DT, and BIM remains unexplored. The following table (Table 3) summarizes the research trends based on keyword association using the Google Scholar web-search engine:

Table 3. Research trends, status in the literature, and opportunity

Research trend	Status in literature	Opportunity
AI+Digital Twin integration	Early-stage, growing fast	Include real-time updates from systems, exploring new sensor materials, and biomimicking certain organizational behaviors
Smart materials data integration	Limited to inexistent	Combine materials behavior data with the engineering lifecycle
Generative AI in engineering design	Emerging	-
Standardization and digital threads	Sparse	Need for interoperable ecosystems

4. Conclusions

This paper presents a comprehensive review of innovative technologies applied in engineering. It focuses on cross-disciplinary fields, with a particular emphasis on digital engineering and AI in engineering systems. The main conclusions are as follows. Digital engineering is moving toward data-based and AI-assisted systems. The latter is essential to sustainable engineering. Rigorous theoretical frameworks, such as many-particle and multiscale models, ensure reliable results and provide the physical and mathematical basis for these systems. While AI helps make predictions faster and handle complex problems. This review highlights how integrating these approaches supports better design, reduced waste, and longer service life of engineered systems. However, multiple obstacles persist when integrating AI models with digital engineering frameworks.

Engineering data are noisy, complex, and sometimes incomplete or inaccessible, which makes it difficult for AI systems to work correctly and requires high data quality. In the meantime, ethical and legal concerns could arise, such as data acquisition and excavation, and the trustworthiness of machine-generated code. In decision-engineering, several AI systems operate as black boxes, where AI-prediction results are hard to understand. Moreover, security risks might emerge, especially in engineering, where handling sensitive industrial data and digital systems can make them vulnerable to data leaks or cyberattacks. Key limitations when integrating digital engineering with AI tools include low data quality, lack of interpretability, complexity of integration at a large-scale industry, and AI often being applied at isolated stages of the product lifecycle. In the smart materials field, there is a large gap between experimental validation and generalized models.

Modern optical networks (DWDM, PON, OTN, ROADM) generate large volumes of operational and physical-layer telemetry data (e.g., OSNR, BER, chromatic dispersion, polarization mode dispersion). This makes them a natural candidate for AI-driven data analytics and intelligent network control. Key AI application domains in optical data transmission include: AI-based adaptive modulation and coding, enabling dynamic adjustment of transmission parameters according to real-time channel conditions; predictive maintenance of optical fibers and components (lasers, amplifiers, connectors) using neural networks and anomaly detection techniques; AI-driven optical path provisioning and routing optimization in ROADM- and SDN-controlled networks; self-healing optical networks, where AI enables fast fault localization and automated service restoration; energy-efficient optical networking, where AI optimizes amplifier power levels and transceiver operation to reduce overall energy consumption.

From a digital engineering perspective, optical networks can be modeled as digital twins of communication infrastructure, where AI establishes a closed feedback loop between the physical layer (fiber, transceivers, amplifiers) and the virtual network model. However, current research lacks comprehensive cross-disciplinary frameworks that jointly address: AI-enabled optical networks, digital twins, BIM, and MBSE approaches for large-scale infrastructures such as data centers, smart cities, and transportation systems. Therefore, AI-assisted optical data transmission represents a critical yet underexplored component of sustainable and resilient digital engineering systems, and should be explicitly addressed as a future research direction.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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