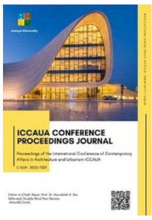

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The Alliance of BIM and Artificial Intelligence: Challenges for a Reinvented Future – The State of the Art

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Abstract

The alliance of Building Information Modeling (BIM) and Artificial Intelligence (AI) is critical for transforming construction management, particularly to fostering more efficient and innovative practices. Despite the progress made in integrating BIM and AI, challenges remain, such as interoperability between different platforms and data structures, as well as concerns over data security concerns when AI algorithms are applied in construction projects. This study aims to examine these challenges and to propose strategies for successfully integrating AI into BIM workflows, enhancing efficiency and safety in construction management. A literature review was conducted to examine research published on the integration of BIM and AI, identifying key challenges, gaps and proposed solutions to improve interoperability, data security and workflow optimization. The study advocates the adoption of standards protocols and unified application programming interfaces (APIs) to improve data exchange between BIM and AI systems. It also highlights the importance of data encryption, AI skills development and a comprehensive training framework within organizations to ensure successful implementation of AI-integrated BIM.
Keywords: Artificial Intelligence; BIM Adoption; Construction Sector; Data synchronisation; Security protocols; AI skills; Digital transformation.

1. Introduction

In the twenty-first century, societies face two major and interconnected challenges: the rapid pace of digitalization and the urgent need for environmental sustainability. As technology advances at an unprecedented pace, industries are undergoing transformations that are reshaping the way we live and work. Simultaneously, growing pressure on resources and the climate crisis are making sustainability a central issue. Artificial intelligence (AI) is playing a growing role, offering new opportunities for innovation and efficiency (Amen 2024), with that, "virtual modelling becomes a vital tool for urban development" (Nafa & Husain, 2021). Balancing the benefits of digitalization and AI with environmental preservation has become a key concern for industries, governments and communities (Goel et al. 2024). The construction sector is at the forefront of this digital shift, driven by advances of the fourth industrial revolution. This context provides an opportunity to explore how tools such as Building Information Modeling (BIM), enhanced by AI, can foster more sustainable and efficient construction practices (Wu et al. 2025).
This study aims to deepen understanding of the barriers to the effective deployment and promotion of BIM and AI integration. By examining the current state of BIM and AI integration, this literature review aims to provide practical recommendations for improving construction efficiency, data security and sustainability throughout the building lifecycle.

2. Material and Methods

A comprehensive review conducted in 2025 aimed to take an in-depth look at the integration of AI and BIM in the construction sector. The aim of the study was to understand how AI and BIM technologies intersect, and to examine the challenges, opportunities and potential new impacts of these technologies on construction management, project efficiency and sustainability.
Primary sources for this study were drawn from three academic databases: Scopus, Google Scholar and Research4Life. The search focused specifically on publications released between 2021 and March 2025, to ensure that the most recent studies on the integration of AI and BIM were collected. These databases were chosen because of their extensive collection of peer-reviewed papers and the increased possibility of accessing free full texts. Search strategies were tailored to each database to ensure that the most relevant and up-to-date studies were collected. The search queries used

were specifically designed for the targeted study of articles related to AI, BIM and their integration into the construction industry. The search terms and queries used are ("AI" OR "artificial intelligence") AND ("BIM" OR "Building Information Modeling") AND ("construction"). On the Scopus platform, the majority of published papers during 2025, were conducted in developed countries, with China accounting for the largest number (n = 50/185). The majority of articles were in the field of engineering, as indicated by subject and number of documents (Figure 1).
The review process using the Rayyan platform (https://www.rayyan.ai/) followed a rigorous selection method to ensure the inclusion of relevant, high-quality studies. Initially, the studies were selected on the basis of their titles and abstracts using Rayyan's filtering system. Duplicate studies were automatically removed in this phase using Rayyan’s deduplication feature. Only studies meeting the pre-defined criteria were selected for further examination and full-text filtering. Rayyan's suggestions, based on Machine Learning (ML), streamlined the selection process by recommending the inclusion or exclusion of articles based on previous selections. After the initial screening, full-text analysis was carried out within the platform, where the articles were downloaded and carefully reviewed for quality and relevance. While Rayyan contributed to the organizational and filtering aspects, the identification of potentials and key challenges in the context of integrating AI and BIM into the construction sector was done manually to ensure a full understanding of the items. The studies were then evaluated on their contribution to the integration of AI and BIM, with a particular focus on identifying industry challenges and proposed solutions.

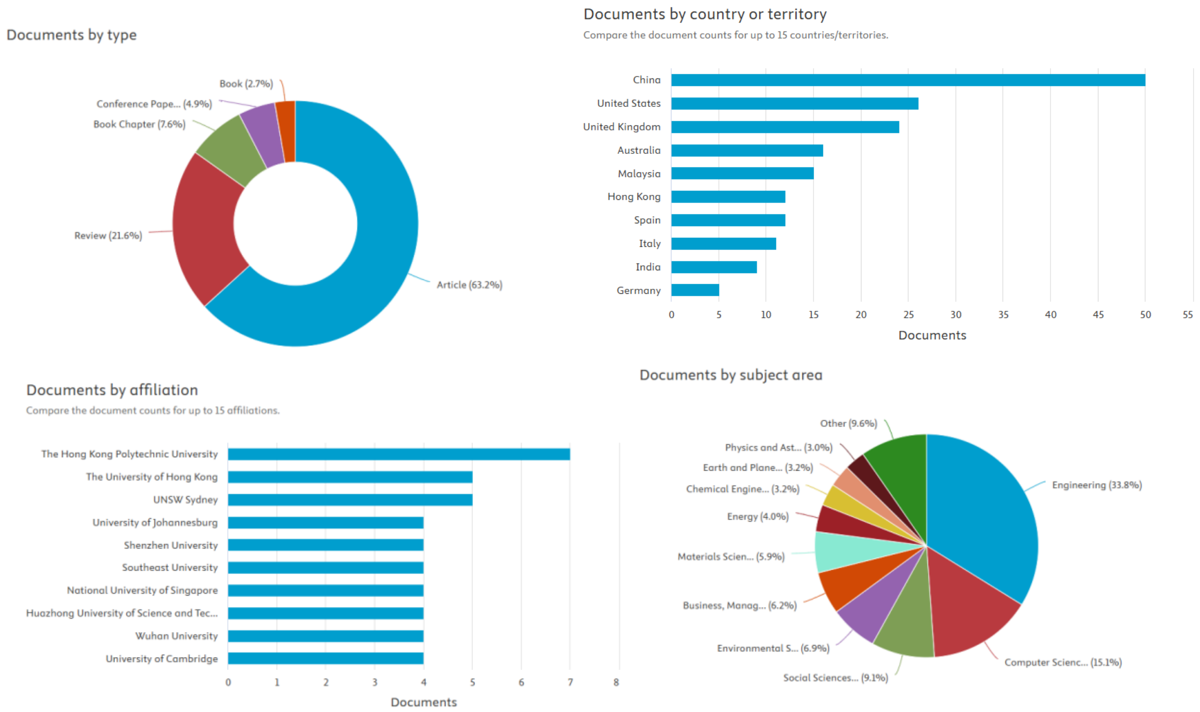


Figure 1. Research Analysis using Search Query Terms on Scopus during 2025 (Scopus data).

3. Results and Discussion

This literature review identifies and presents current knowledge related to the integration of AI and BIM. The findings from the included studies were grouped into two main themes after presenting the conceptual frameworks of BIM and AI: (1) the benefits of AI and BIM integration throughout a building's lifecycle, and (2) the challenges and barriers to integrating BIM and AI, such as interoperability challenges, data security concerns, data quality and standardization and workflow issues. Additionaly, strategies proposed to overcome these integration challenges for a suistainable alliance between BIM and AI were discussed.

3.1. Conceptual Framework: Toward the Convergence of BIM and Artificial Intelligence

Building Information Modeling/Management

BIM, as a digital information management process, has evolved from basic 3D modeling tools to a comprehensive solution for managing a building's entire lifecycle, from design and construction to operation and maintenance. During the design phase, BIM enables the creation of detailed and accurate models, as well as the rapid detection and resolution of potential issues. It reduces the probability of design errors and conflicts, helps detect clashs and optimize design alternatives, while improving visualization. It also integrates relevant data into a shared or common data environment (CDE), facilitating collaboration among stakeholders. During the construction phase, CDE enables better coordination between architects, engineers, contractors and other stakeholders, improving resource management, scheduling and costs, among other factors. Once the building is completed, BIM continues to play a key role during the operational phase, centralizing equipment management, predictive maintenance and energy optimization within a single commun environment, ensuring traceability and optimal management. At the end of the building’s life cycle, BIM facilitates planning for renovations or demolitions, enabling the efficient reuse of data collected throughout the entire cycle. At every stage, BIM enables centralized and shared information management, fostering collaboration among all stakeholders and significantly reducing the likelihood of errors by ensuring consistent and accurate data throughout the project (Altwassi et al. 2024). BIM dimensions, which refer to the gradual addition of information and functionalities to the basic 3D model, have evolved to include dimensions: 4D (integrating time for planning and tracking tasks), 5D (integrating cost), 6D (integrating durability) and 7D (integrating management) which are the standard dimensions as well as the dimensions D8, D9 and D10 which are new and not yet standardized (Figure 2).

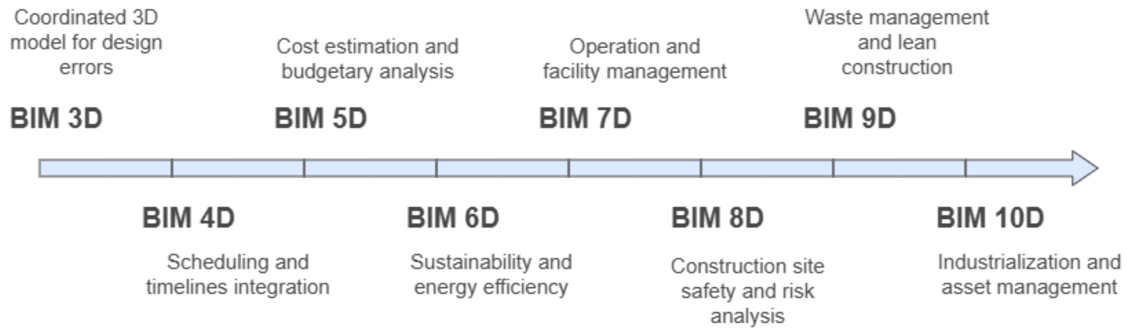


Figure 2. BIM dimensions (Inspired from Revit BIM SerVice).

Artificial Intelligence

AI refers to the set of techniques that enable computer systems to simulate human cognitive processes such as learning, decision making, pattern recognition and problem solving. It is mainly based on ML, which allows systems to improve their performance based on data and previous experiences, without being explicitly programmed (Softaoğlu, 2024a; Softaoğlu 2024b). Different categories of AI can be distinguished (Figure 3) (https://www.ibm.com). Five categories of ML models can be identified. Learning from labelled data to train algorithms to predict or classify new data is supervised ML (SL). Learning patterns from data without labels known as unsupervised ML (UL) is used to analyze and cluster unlabeled datasets with the ability to discover similarities and differences in information (clustering and dimensionality Reduction). Semi-supervised ML combines a small amount of labeled data with a large amount of unlabeled data for training to guide classification and feature extraction from the larger unlabeled datasets. Reinforcement ML (RL) model that is similar to SL learns by using trial and error. A sequence of successful outcomes will be reinforced to develop the best recommendation or policy for a given problem. As exemples, Q-Learning is a model-free RL algorithm for learning action-value functions and Policy Gradient Methods focuses on optimizing the policy directly, instead of the value function, to make decisions and maximize long-term rewards. Self-supervised learning (SSL) is a ML that uses UL for tasks that conventionally require SL to generate implicit labels from unstructured data (learning by distinguishing between similar and dissimilar pairs of data points or contrastive learning). SSL is particularly useful in computer vision and natural language processing (NLP). A number of ML algorithms including Neural networks, Linear regression, Logistic regression, Clustering, Decision trees and Random forests are commonly used.

Deep Learning involves neural networks with many layers (deep neural networks) to model high-level abstractions. In contrast to ML that utilize simple neural networks with one or two computational layers, deep learning models employ three or more layers, usually consisting of hundreds or even thousands of layers, to train the models. Deep learning drives many applications to improve automation. Deep learning algorithms are complex including different types of neural networks to address specific problems or datasets (n>6). Deep learning encompasses a variety of model types, including Feedforward Neural Networks (FNN) the basic type of neural network with a simple flow from input to output, Convolutional Neural Networks (CNNs) for image and video processing, Recurrent Neural Networks (RNNs) for sequence data such as language and speech, Autoencoders and Variational Autoencoders (VAEs) for data compression and generation, Generative Adversarial Networks (GANs) for creating realistic data, Diffusion Models for image generation and denoising, and Transformer Models for advanced natural language processing, each with its own strengths and challenges in terms of accuracy, scalability, and computational complexity.

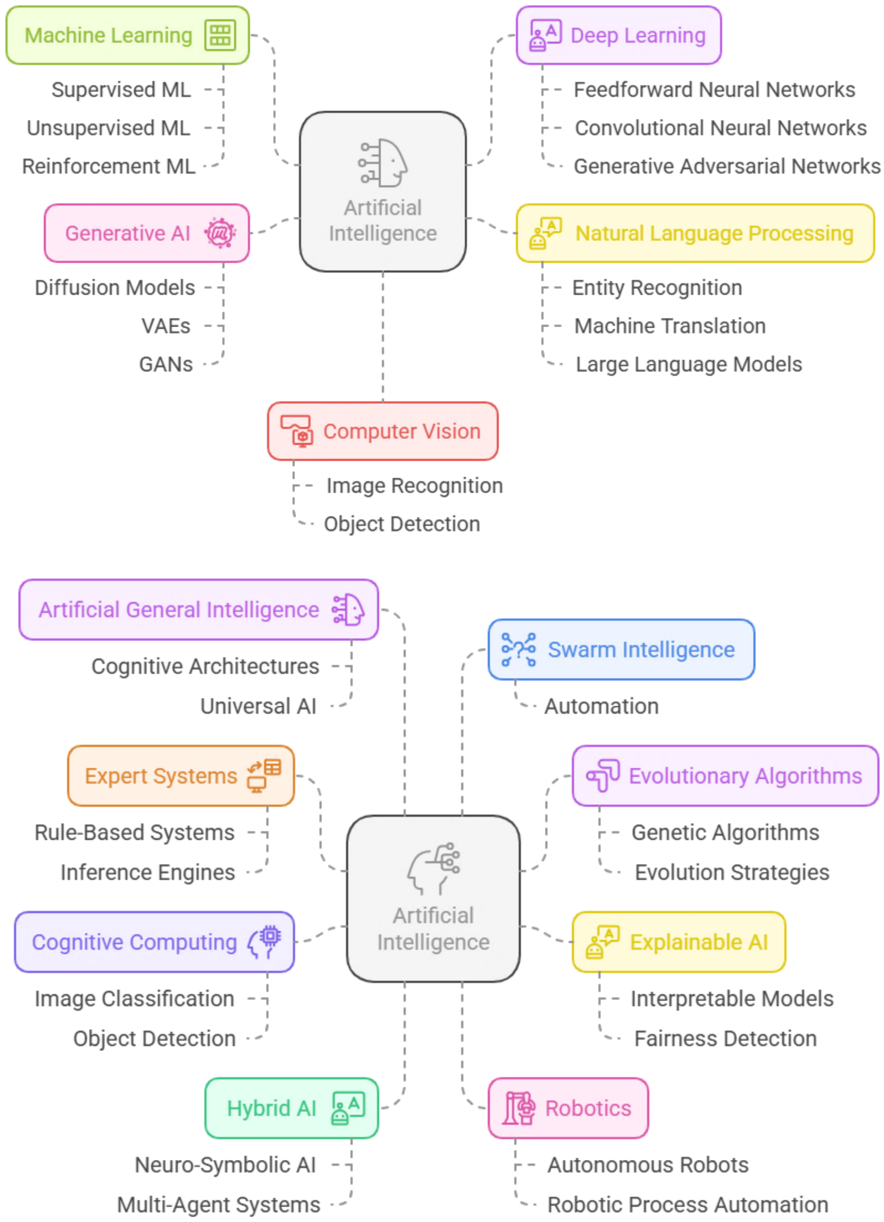


Figure 3. AI Categories.

Natural Language Processing (NLP) is a subfield of AI, and it can be approached using both traditional ML models and deep learning techniques, with deep learning now being the dominant method for state-of-the-art performance. NLP focuses on enabling machines to understand, interpret, and respond to human language such as Text Classification, Named Entity Recognition (NER), Machine Translation, Question Answering, Speech Recognition and Text Generation (e.g., chatbot dialogues, writing assistants). Large Language Models (LLMs), like GPT-4, are particularly effective in these tasks, pushing the boundaries of what's possible in language-based AI applications. One of the most notable advancements within deep learning is the development of LLMs, which have revolutionized NLP by enabling machines to generate and understand human language at an unprecedented scale. Generative AI refers to an AI that enables users to quickly generate new content based on a variety of inputs (https://www.nvidia.com). Inputs and outputs to these models can include text, images, sounds, animation, 3D models, or other types of data. Generative AI models use neural networks to identify the patterns and structures within existing data to generate new and original content. Diffusion models, VAEs, GANs, and transformer networks are key types of generative models in AI. Deepfake technology uses generative models like GANs to create realistic fake content, such as videos and images. Language models, like GPT, generate human-like text, enabling applications such as chatbots, content creation, and text summarization. Computer Vision, according to IBM, is a branch of AI that employs ML and neural networks to enable computers and systems to interpret and understand visual information (digital images, videos, etc…) allowing image classification, object detection, semantic segmentation, face recognition and optical Character Recognition (OCR), to make recommendations or take action when defects or issues are detected. Computer vision is used in industries that range from energy and utilities to manufacturing and automotive. Expert Systems (ES) simulate human expertise in decision-making. An ES is a computer program that uses AI technologies and employs specific knowledge about a narrow domain stored in the expert system's knowledge base. An ES is divided into two subsystems: a knowledge base and an inference engine. Application areas include classification, diagnosis, monitoring, process control, design, scheduling and planning, and

generation of options. ES include Rule-Based Systems (systems that use predefined rules to make decisions), Inference Engines (components of expert systems that apply logical reasoning to make decisions and Knowledge Representation (semantic networks, ontologies, etc…).
Evolutionary Algorithms are evolutionary AI-based computer applications that solve problems by employing processes that mimic the behaviors of living things. The family of evolutionary algorithms includes Genetic Algorithms (GA), Genetic Programming (GP), Differential Evolution, Evolution Strategies, and Evolutionary Programming. Explainable AI (XAI), according to IBM, is a set of processes and methods that allows human users to comprehend and trust the results and output created by ML algorithms. It aims to make AI model decisions more understandable and transparent, incorporating techniques like interpretable models, post-hoc explanations (SHAP values, LIME), and fairness/bias detection. Explainable AI is one of the key requirements for implementing responsible AI, a methodology for the large-scale implementation of AI methods in real organizations with fairness, model explainability and accountability. Swarm Intelligence is a form of AI inspired by the collective behavior of natural organisms like ants. It involves decentralized, self-organized systems where individual agents share information and make decisions collectively without central control. This approach allows devices to process and react to data in real time, enhancing adaptability, flexibility, and responsiveness. Swarm intelligence is particularly useful in dynamic environments and it is applicable in areas like automation. Swarm Intelligence algorithms have become increasingly popular due to their ability to find optimal solutions in complex and large-scale environments. These algorithms are particularly effective in fields like supply chain optimization, where they help improve logistics, resource allocation, and route planning. Cognitive Computing seeks to simulate human cognition and improve human-computer interaction (HCI) with technologies such as speech recognition and gesture control. Hybrid AI integrates multiple AI approaches, like Neuro-Symbolic AI, Multi-Agent Systems, and Logic-based AI, to overcome the limitations of individual methods. Robotics applies AI in various forms, from autonomous robots performing tasks independently, to robotic process automation (RPA) streamlining business processes, and swarm robotics coordinating multiple robots to collaborate on tasks. Besides these type of narrow AI highly specialized for particular tasks, Artificial General Intelligence (AGI) is considered a hypothetical concept that envisions machines capable of performing any intellectual task that humans can, with approaches like Cognitive Architectures (SOAR and ACT-R cognitive architectures) and Universal AI working toward this goal (Xu et al. 2023).
AI's advanced capabilities in data analytics and automation are revolutionizing the way projects are designed, planned and executed. By relying on algorithms that learn from data, analyze complex information, and make autonomous or semi-autonomous decisions, AI improves the accuracy and efficiency of project management. This integration allows for real-time decision-making, simulation and predictive forecasting with remarkable accuracy. AI applications are broad, ranging from intelligent architectural design systems to optimized energy management and predictive infrastructure maintenance.

3.2. AI and BIM integration

Building Information Modeling (BIM) has profoundly transformed the architecture, engineering and construction (AEC) sector, providing professionals with tools to design and simulate structures with unrivalled accuracy, while revolutionizing data management throughout the building lifecycle (Figure 4). It is based on a coherent integration of policies, processes and technologies, constituting a structured methodology for building information management.
The integration of artificial intelligence (AI) into BIM considerably enhances its potential, introducing innovative capabilities at every phase of the project. Thanks to AI's computing power and learning mechanisms, it becomes possible to improve decision-making, optimize processes, enhance the sustainability of structures, and raise overall building performance.
This integration, throughout the entire life cycle - from design to construction, then to post-construction management (operation, maintenance, deconstruction or recycling) - opens up major prospects for the evolution of the sector (Figure 5). AI-enhanced BIM tools can generate dynamic models of building infrastructure, which can be used in real time to monitor construction progress, anticipate maintenance needs and improve occupant comfort.
The convergence of BIM and AI is thus initiating a fundamental transition in construction project management, promoting more efficient, innovative and sustainable approaches. AI enhances BIM functionalities by automating certain critical tasks, such as detecting and resolving design conflicts at an early stage. It can also analyze historical data to predict potential delays, optimize schedules and anticipate long-term maintenance needs. In addition, ML models can be used to improve the quality of designs, whether in structural, energy or economic terms, through the simulation of alternative scenarios. This technological synergy contributes not only to improving the construction process, but also to extending the lifespan of buildings and their equipment, encouraging more sustainable and efficient practices across the sector (Khan et al., 2024; Jiang et al., 2024).
Nevertheless, the effective integration of BIM and AI still faces numerous technical, commercial, cultural, organizational and practical obstacles, requiring a structural adaptation of methods and mindsets in the construction industry.

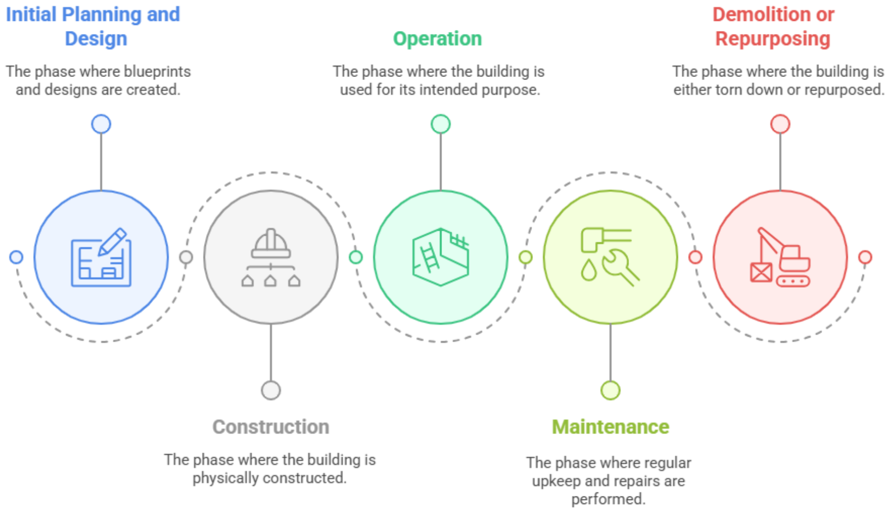


Figure 4. Building Lifecycle Management.

By looking at the key stages of the life cycle, we will address how these technologies have revolutionized management practices and optimized construction projects.

The design phase

The design phase is crucial because it lays the foundation for a building's efficiency, sustainability, and functionality. AI plays a key role in optimizing the design process, minimizing wasted resources, and improving collaboration. Generative AI with BIM is revolutionizing design workflows, replacing traditional sequential design processes with iterative creative cycles (Onatayo et al. 2024, Chengyuan et al. 2025). Generative AI, particularly algorithms such as GANs and VAEs, is essential in this phase, as it allows architects to generate complex designs from provided parameters. For example, GANs can create designs that optimize natural light and energy efficiency (Xiong et al. 2025), while VAEs help explore various configurations in terms of materials and shape by adjusting input parameters (Ghimire et al. 2024). AI tools can simulate multiple solutions in record time, offering more innovative and efficient alternatives than traditional methods. Moreover, evolutionary algorithms, such as GA, assist in design optimization by taking into account factors such as adjacency requirements, traffic flow, and natural lighting (Koçak et al. 2023). The integration of AI with parametric modeling is transforming the design process by creating dynamic real-time simulations that adjust based on environmental data and material constraints. AI tools enable architects to design adaptable structures that take into account variables such as changing climatic conditions and urban development trends, thereby improving energy efficiency and structural integrity (Wu et al. 2025). For example, SL can analyze past building performance data to inform future design choices, while RL helps test different scenarios to optimize building layouts (Mahmood et al. 2024). AI tools can also improve energy efficiency by optimizing systems such as heating, ventilation, and air conditioning (HVAC), adjusting them to the actual use of the building, and enhancing sustainability by optimizing, for example, the layout of the building's windows to reduce dependence on artificial energy systems (Manmatharasan et al. 2025). Moreover, AI helps identify potential conflicts during the design phase using technologies such as computer vision. This allows for the detection of problems in 3D renderings or models, ensuring that design errors are corrected before the construction begins (Ahmadpanah et al. 2022). This technology goes beyond simple visual verification by comparing BIM models with dynamic simulations, thereby allowing the identification of anomalies that manual methods might miss (Pan et al. 2023). In parallel, expert systems, relying on specialized knowledge bases, assist architects and engineers in validating design choices in compliance with regulatory and environmental standards. These systems offer intelligent recommendations, ranging from the selection of the most appropriate materials to compliance with local energy and environmental standards (Burggräf et al. 2021, Esfahani et al. 2022). The optimization of building space layout using AI relies on advanced technologies such as ML, RL. GANs have been applied to tasks such as floor plan generation, highlighting their potential to automate and improve space planning tasks (Tanasra et al. 2023). ML can analyze human movements within a space and predict how layout adjustments, such as widening corridors or repositioning doors, will influence traffic flow. RL, on the other hand, allows AI to explore different layout configurations and learn which choices minimize congestion while meeting the specific needs of the building (Pan et al. 2023). By combining these technologies, AI ensures more efficient and functional spaces that meet not only technical requirements but also the comfort and safety of the occupants (Alavi et al. 2024).

Furthermore, AI enhances the BIM workflow by integrating virtual assistants powered by NLP, thereby facilitating user interaction with the system. These assistants can interpret user commands, such as voice commands, and extract relevant data, thereby accelerating decision-making. LLMs and AI-based chatbots help summarize construction contracts and generate documents, facilitating better understanding and faster decision-making (Zheng et al. 2023, Ghimire et al. 2024). In engineering, AI helps generate technical specifications, perform complex calculations, and simulate real-world conditions, such as material strength or thermal flows, to optimize designs and ensure safety. Systems like StructGAN are particularly useful in structural design, ensuring safety and cost-effectiveness in civil engineering (He et al. 2025). Moreover, SL can predict long-term operational costs based on the chosen materials and configurations, allowing engineers to make more cost-effective choices during the design phase (Nguyen et al. 2025).

Overall, the integration of AI with BIM during the design phase accelerates project completion, improves building performance, and ensures sustainability. AI tools and algorithms optimize every aspect of the design process, from layout planning and material selection to energy efficiency and cost management. This transformation not only improves the design process but also ensures that buildings are better prepared to meet future needs and environmental challenges (Chengyuan et al. 2025, Li et al. 2025).

The construction phase

BIM offers numerous advantages during the construction phase, in particular when extended to include advanced dimensions such as BIM 4D (time planning), BIM 5D (cost estimation), BIM 6D (sustainability), and BIM 8D (safety) (Raza et al. 2023). BIM 4D enhances scheduling and logistics management by integrating the time dimension, facilitating better coordination among teams and early detection of potential conflicts. This significantly reduces errors, minimizes delays and ensures smooth on-site progress (Awe et al. 2025). BIM 5D enables costs to be accurately estimated in real time, taking into account historical data and adjusting forecasts as the site evolves, helping to keep the budget under control and avoid overruns (Safaa Eldin et al. 2024, Banihashemi et al. 2022). BIM 6D focuses on sustainability, analyzing the environmental impact of materials and construction choices, helping to reduce carbon footprints and promote responsible building practices (Al-Raqeb et al. 2025, Lu et al. 2024). BIM 8D emphasizes safety by simulating risk scenarios and integrating preventive tools to reduce the likelihood of accidents and promote a safer construction environment (Manzoor et al. 2025).

When BIM is coupled with AI, these benefits are amplified considerably. SL algorithms can predict the risk of delays or cost overruns based on historical data, enabling managers to take preventive action before a problem occurs (Egwim et al. 2024, Turkyilmaz et al. 2024). UL can be used to analyze data in real time and detect anomalies on site, such as errors in materials management or execution problems, thus reducing inefficiencies (Asif et al. 2024). In fact, AI can analyze weather conditions, material shortages and other variables to predict risks such as delays, cost overruns or safety issues. This information enables project managers to implement proactive strategies and avoid costly setbacks. What's more, AI-powered algorithms can detect anomalies or errors in real time during the construction phase, enabling immediate corrective action to be taken, reducing the likelihood of accidents or costly mistakes. AI can improve construction site management by monitoring progress and performance in real time. Using sensors, drones and cameras, AI can process data collected on site and compare it with the BIM model to ensure that construction is proceeding as planned. AI can flag up any anomalies, such as incorrect use of materials, structural problems or failure by workers to observe safety protocols. This real-time feedback enables faster decision-making and intervention where necessary. Generative AI and CNNs enable automated site inspection, detecting construction defects or deviations from plans using image recognition, improving quality control. Integrating technologies such as drones, IoT sensors, and computer vision with BIM allows for real-time safety monitoring on construction sites, enabling the rapid identification of hazards or abnormal behavior (Al-Sabah et al. 2024). BIM 8D benefits greatly from AI to identify safety risks before they become problematic, simulating hazard scenarios and intervening in real time to prevent accidents. In addition, the use of autonomous and collaborative robots for tasks such as material transport or visual inspections increases worksite efficiency while reducing workers' exposure to hazardous environments (Yan et al. 2024). In short, the integration of BIM and AI transforms construction site management into a more intelligent, predictive, and secure process. The AI-enhanced dimensions of BIM 6D and BIM 8D enable not only optimized management of resources, safety and costs, but also proactive anticipation of problems, contributing to sustainable construction practices with more efficient, safer and environmentally-friendly construction phase (Al-Raqebet al. 2025). In this sense, while Industry 4.0 focused on automation and efficiency, with humans guiding the use of technology, in the future Industry 5.0 introduces a new paradigm in which intelligent machines and humans collaborate more closely. It puts artificial intelligence at the service of people, promoting a more human-centered, sustainable and resilient industrial ecosystem (Askar et al. 2024).

The operation and maintenance phases

During the operation and maintenance phases of a building lifecycle, BIM enables proactive and efficient building management. In fact,using BIM 6D and BIM 7D, specifically designed to integrate information related to equipment maintenance, it is possible to provide a maintenance schedule and track the history of each intervention on building systems. This makes it easier to plan maintenance interventions, anticipate failures and optimize the lifespan of installations, while enabling real-time monitoring of the condition of equipment and installations (Mostafa et al. 2023).

Integrating AI and BIM in the operation and maintenance phases adds significant value by optimizing building performance, reducing energy consumption and facilitating smarter space management. AI can analyze real-time data collected by sensors (temperature, humidity, occupancy, lighting) to optimize energy use. ML models can adjust HVAC systems, lighting and other installations to reduce energy consumption while maintaining occupant comfort (Hosamo et al. 2024). In addition, AI can analyze occupancy tracking data to optimize space utilization, suggest reconfigurations based on actual occupancy patterns, or predict future space requirements based on historical trends. By integrating this data into the BIM model, AI enables not only proactive energy management, but also more efficient use of space, contributing to the construction of more sustainable buildings that better meet the needs of occupants (Di Giuda et al. 2024). In addition, AI plays a key role in predictive maintenance by using BIM sensor data to anticipate failures of critical equipment (elevators, HVAC systems, plumbing). For example, SL algorithms can predict when equipment is likely to fail based on historical and sensor data, enabling managers to carry out proactive maintenance, reduce unplanned breakdowns and optimize equipment life. Planning interventions before major problems occur reduces maintenance costs and minimizes operations. Finally, AI enhances the occupant experience by automatically adjusting environmental factors such as temperature and lighting based on user preferences and real-time data collected by the BIM. Integrating IoT, sensors and AI algorithms into the BIM model enables the collection of actionable data, making building management smarter and more efficient. Specific AI subtypes such as ML/ SL and predictive analytics play key roles in energy optimization, predictive maintenance and space management. For example, reinforcement learning can be used to improve HVAC control systems based on continuous feedback, while computer vision can help monitor occupancy patterns to better allocate space (Mostafa et al. 2023, Hosamo et al. 2024, Mehraban et al. 2024). AI-enhanced BIM ultimately results in buildings that are more energy-efficient, more cost-effective and better adapted to the needs of their users.

The decommissioning phase

The end-of-life phase of a building includes renovation, rehabilitation, waste management, materials recycling and planning for demolition or renovation of the building. BIM and AI technologies play a role in intervention planning and resource management, while optimizing sustainability and materials management. AI can track the performance and material composition of buildings throughout their lifecycle, providing insights that can help with future renovations or demolitions.

Renovation & retrofitting phase:

Buildings often require renovations or upgrades to remain functional, durable and energy-efficient as they age. In this context, BIM plays an essential role in guiding these processes. By providing a detailed digital representation of the building, BIM enables precise planning and management of renovation activities, ensuring that all components are taken into account and optimized (Doukari et al. 2023). When integrated with AI, BIM can significantly improve the effectiveness and efficiency of renovations (Mulero-Palencia et al. 2021). For example, ML algorithms can analyze existing building data, including structural integrity, energy performance and material condition, to identify areas in need of improvement and propose optimal solutions. Thanks to predictive AI, tools such as TensorFlow or Scikit-learn can estimate the remaining lifespan of systems such as heating, HVAC, and suggest preventive measures even before failure occurs (Gourabpasi et al. 2024). While BIM 5D enables real-time financial management, the integration of dynamic cost data powered by AI tools makes it possible to track expenses throughout the renovation process, adjusting forecasts according to changes in material and labor prices
(Lins et al. 2024). By analyzing the environmental impact of materials and construction methods (BIM 6D), AI tools such as Green Building Studio or EnergyPlus can simulate a building's energy performance and suggest more efficient solutions, such as improving insulation, installing solar panels or adopting more efficient heating and cooling systems (Piras et al. 2025). What's more, AI-based predictive analytics can forecast the future performance of critical building systems, such as the elevator or plumbing pipes. Predictive maintenance software such as Uptake or IBM Maximo can detect anomalies in the data collected by IoT sensors and alert building managers to potential problems well before they occur, enabling preventive maintenance interventions to be planned. AI can also be used to optimize the choice of materials. For example, AI-based systems can analyze the sustainability of materials in terms of their carbon footprint, ability to be recycled and overall environmental impact, facilitating greener, more economical decisions. In the renovation and upgrading phase, AI-enhanced BIM allows for optimizing energy efficiency, the selection of sustainable materials, and the planning of long-term maintenance strategies. AI and energy modeling tools, such as OpenStudio or DesignBuilder, can predict the energy impact of different building configurations before work begins, thereby ensuring long-term cost reduction (Muta et al 2025). This combination ensures that the building remains sustainable, functional, and energy-efficient throughout its lifecycle. By integrating these tools into the renovation process, it becomes easier to make the building more eco-friendly, more cost-effective, and better suited to the future needs of the occupants. This makes the renovation process smoother, more cost-effective, and environmentally friendly, while maximizing the lifespan of the facilities and reducing operational risks.

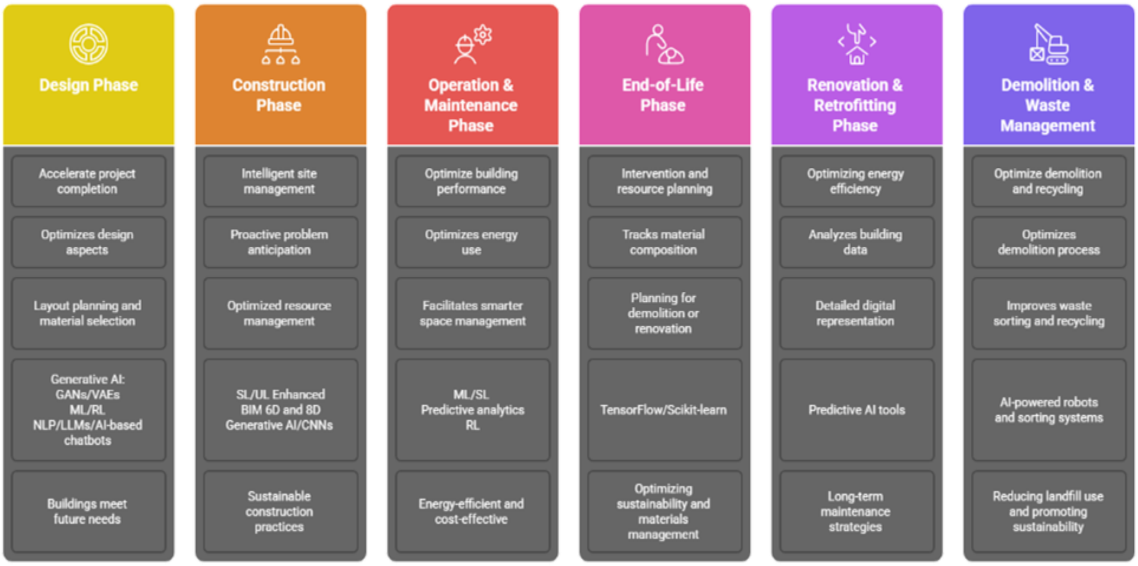
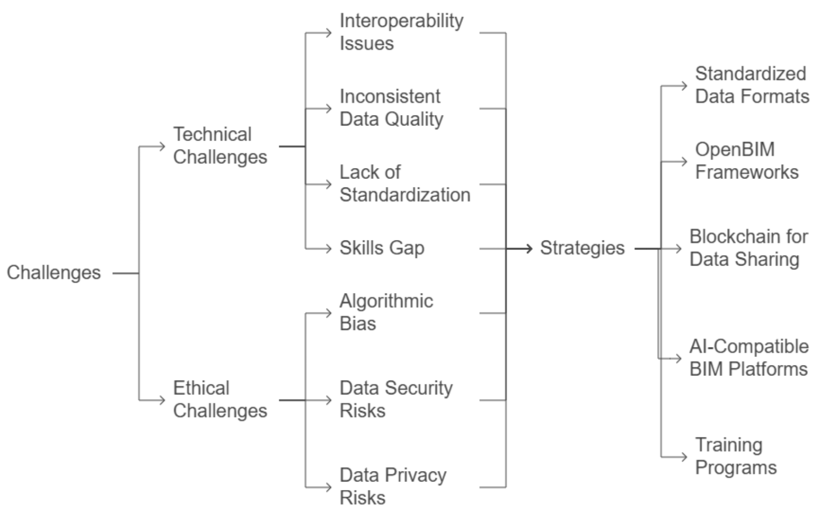


Figure 5. AI and BIM integration throughout the building lifecycle phases.

Demolition and waste management:
Once a building has reached the end of its life, AI can help optimize demolition, waste management, and recycling processes. AI can assist in planning demolition activities, ensuring that materials are recovered and recycled. AI systems can optimize the demolition process by identifying the most efficient and safest methods for deconstructing a building while minimizing environmental impact. This includes determining which materials can be recycled and which should be disposed of, contributing to sustainability goals. AI improves waste sorting and recycling. AI-powered robots and sorting systems can automatically separate construction waste (e.g., metal, wood, concrete) for recycling, reducing landfill use and promoting sustainability. ML models can predict which materials are most likely to be reused or recycled (Lins et al. 2024).

3.3. AI and BIM integration challenges and barriers

Despite the numerous advantages of combining BIM and AI, several challenges must be addressed for this integration to reach its full potential (Liang et al. 2024, Heidari et al. 2023, Khan et al. 2024) (Figure 6). However, despite many advances, significant research gaps remain particularly in practical implementations and real case studies to validate the theoretical frameworks. Additional research is also needed to assess the long-term impact of AI integration on project performance, as well as to establish ethical guidelines ensuring transparency, fairness, and data confidentiality.
The effectiveness of AI relies on access to reliable, consistent, and large quantities of data. However, in the construction sector, data often comes from multiple sources (IoT sensors, modeling software, etc.) and is rarely standardized. This lack of standardization hinders the interoperability of tools and prevents a smooth integration between AI and BIM systems (Figure 7). As BIM models become richer in information and AI leverages increasing volumes of sensitive data (proprietary plans, schedules, financial data, etc.), cybersecurity risks are intensifying. It is essential to protect this data against unauthorized access, leaks, and cyberattacks. Moreover, the management of personal data such as presence of occupants and video surveillance requires adherence to strict standards of confidentiality and consent (Figure 7).



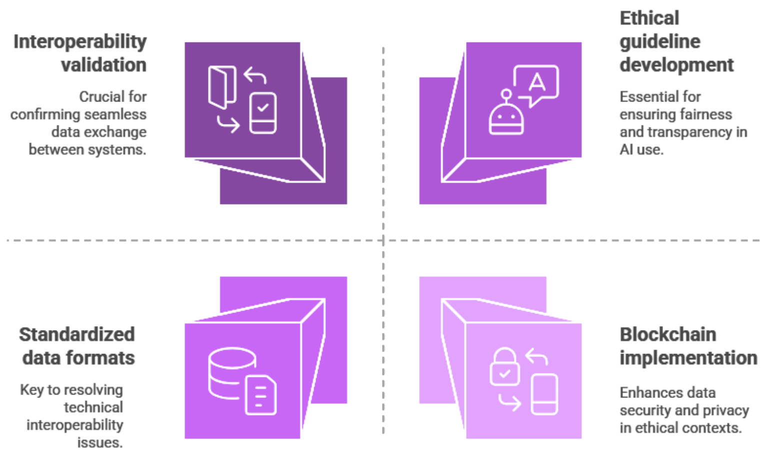


Figure 6. The challenges of BIM and AI integration in construction sector and strategies to adrees them.

Legend: The main obstacles include both technical and ethical issues. Technically : 1. Interoperability issues between platforms and data structures 2. inconsistent data quality 3. Lack of standardization 4. significant skills gap that requires workforce training and upskilling. Ethically: 1. Algorithmic bias 2. risks to data security .3 risk to data privacy. Strategies and technologies to address the challenges of integrating AI with BIM. 1. The use of standardized data formats to improve interoperability 2. The adoption of openBIM frameworks 3. The implementation of blockchain for secure data sharing 4. The development of AI-compatible BIM platforms 5. The promotion of training programs and upskilling initiatives to bridge the skills gap in the workforce.

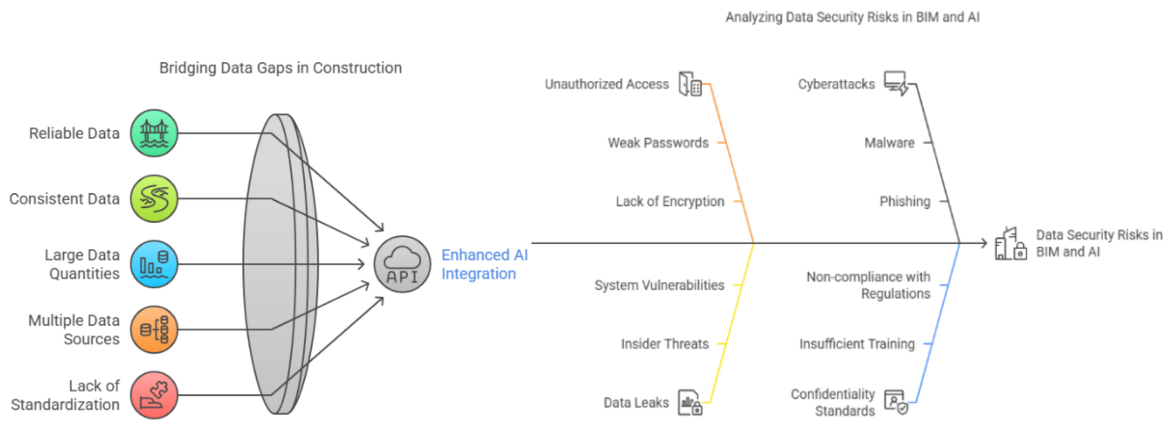


Figure 7. (Right) Quality, consistency, and interoperability of data (Left) Data security and confidentiality.

The effective integration of AI into BIM processes requires a skilled workforce. However, many construction professionals do not yet possess the necessary skills to handle these advanced technologies. Moreover, a certain cultural resistance hinders the adoption of AI, perceived as too complex or threatening to traditional methods. **T**he implementation of BIM-AI solutions involves significant costs: purchasing software, hardware, staff training, maintenance, etc. This can represent a major obstacle, especially for SMEs in the sector. However, the potential long-term gains in terms of productivity, quality, and risk reduction can far outweigh this initial investment. It is therefore essential to demonstrate the return on investment (ROI) through pilot projects and successful case studies. To overcome these challenges many solutions have been reported. In fact, this ensures that all stakeholders have access to consistent information in real-time. Moreover, the use of blockchain, combined with robust encryption protocols, allows for the securing of sensitive data. AI solutions dedicated to cybersecurity can also detect threats in real-time and ensure proactive protection of systems. The use of secure cloud is also a key solution (celik et al. 2023). To improve data quality through AI, AI algorithms can be used to clean, structure, and normalize data from different sources. This ensures their consistency before integration into BIM models, thereby providing more accurate predictions and more reliable decisions. Finally, creating standardized interfaces, open-source APIs, and development kits (SDKs) will facilitate communication between AI algorithms and BIM platforms. This will enable real-time access to data while preserving the integrity of the models. The development of ML platforms tailored to BIM will also facilitate this integration (Singh et al. 2024).

4-Conclusion

Far from being futuristic, BIM and AI technologies are already widely deployed, as our review shows, and their synergy promises to meet the challenges of sustainability, resource optimization and intelligent urban development throughout the lifecycle of buildings and infrastructures. However, the adoption of AI is not without its challenges, particularly in terms of interoperability, data security and streamlined workflows. In addition, the integration of AI and BIM raises several ethical considerations. The main concerns relate to the management of data confidentiality, particularly sensitive data collected during the design and the construction of buildings. The security of AI systems is also a major challenge, as is the risk of bias in algorithms that could lead to unfair decisions, particularly in resource allocation or planning. Furthermore, the successful integration of AI into the construction sector requires a structured approach, starting with an assessment of specific business needs and objectives, followed by training professionals, adapting existing processes and keeping up to date with technological advances to ensure continuous improvement and compliance with industry standards. Understanding the applications and limitations of BIM and AI technologies is crucial for organizations seeking to harness the full potential of these innovations in order to ensure the ethical use of AI and adhere to appropriate regulations to mitigate AI-related risks (Liang et al. 2024, Heidari et al. 2023).

Integrating AI generative design tools into BIM is one of the most exciting benefits. This could lead to the creation of highly innovative, sustainable and efficient buildings, tailored to specific environmental and functional needs. In addition, advances in robotics, automation and AI-powered construction techniques could streamline the construction process, reducing labor costs and improving safety. In facilities management, AI-powered BIM models could evolve into fully autonomous systems that continuously monitor building performance, forecast maintenance needs and even manage energy consumption in real time. This could lead to smarter, more sustainable buildings that operate at peak efficiency.

As AI technologies continue to advance, the alliance between BIM and AI is set to redefine the construction sector, offering more significant opportunities for innovation, efficiency and sustainability. Looking ahead, the rise of general artificial intelligence could further revolutionize the sector. An AGI system, capable of learning and reasoning across all disciplines - architecture, engineering, sustainability and construction management - could autonomously manage the entire life cycle of a project. It could identify clashes and conflicts, minimize costs and carbon footprints, and dynamically coordinate project stakeholders in real time. Although Artificial Superintelligence (ASI) remains a theoretical concept, progress towards AGI is already heralding a transition to Industry 5.0 and an era that emphasizes collaboration between humans and intelligent systems, sustainability, ethics and inclusivity. The vision of Industry 5.0, which aims to place human well-being at the center of manufacturing systems, achieves social goals beyond employment and growth, to ensure sustainable prosperity for the sustainable development of all humanity (Figure 8). By integrating BIM and AI within this framework, the construction sector can not only automate and optimize processes, but also enhance collaboration, safety and adaptability to societal needs. However, to realize the full potential of this partnership, the sector needs to address key challenges, such as data quality, standardization, workforce training and investment. Once these obstacles are overcome, the future of construction will undoubtedly be shaped by the powerful combination of BIM and AI within the Industry 5.0 paradigm, radically transforming the way buildings are designed, constructed and operated (Akhavan et al. 2025).

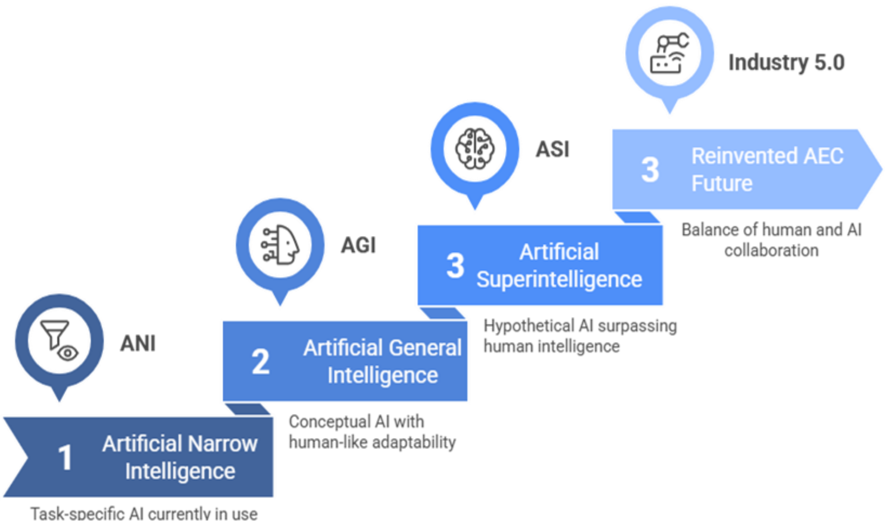


Figure 8. Evolution of AI towards Industry 5.0.

Conflict of Interests

The Author(s) declare(s) that there is no conflict of interest.

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