

Title: BIM and AI integration in AEC Industry: a systematic review

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Abstract:

Building Information Modeling (BIM) has revolutionized the architecture, engineering, and construction (AEC) industry, offering a unified, data-driven approach to managing projects throughout their lifecycle. The emergence of Artificial Intelligence (AI) has opened new possibilities for BIM, enabling advancements such as improved design methodologies, optimized resource management, predictive analytics, and automated decision-making [1]. This paper delves into the synergy between BIM and AI by systematically reviewing recent articles from 2023 to 2024. By analyzing AI-driven applications across different phases of AEC projects, it highlights how AI can address BIM weaknesses. Key findings underscore the transformative potential of BIM-AI integration while addressing current challenges and gaps in the field. The study concludes with a forward-looking discussion, identifying future research opportunities to drive the adoption of these innovative technologies in AEC workflows.

Keywords: BIM, AI, AEC, building management, design management.

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1. Introduction

1.1 BIM and Its Role in AEC

Building Information Modeling (BIM) has increasingly emerged as a foundational element within the domains of architecture, engineering, and construction (AEC), as it significantly helps a more cohesive and combined methodology for the processes involved in building design, construction, and management throughout the entire lifecycle of a project. By enabling the development of detailed, data-enriched digital representations of a structure, BIM markedly enhances the quality of communication, coordination, and informed decision-making among diverse project teams, thereby promoting a more balanced working environment that is favorable to successful project outcomes [2], [3]. This innovative approach effectively addresses long-standing waste that have historically plagued the AEC sector, including but not limited to the commonness of errors stemming from disjointed communication channels and the slow pace of decision-making processes that can hold back project timelines and budgets. Through the consolidation of critical information within a digital model, BIM significantly augments the precision and overall efficiency of design, construction, and operational methodologies, thereby fostering a more efficient workflow that benefits all stakeholders involved in the project [3], [4], [5].

The transformative influence of BIM in the AEC industry is illustrated by its capacity to promote enhanced collaboration among various participants, generate cost savings through optimized resource management, and ensure a higher degree of accuracy in the execution of projects from inception to completion [2]. Because of that, it is important to acknowledge the challenges that must be defeated in order to fully take advantage of the vast potential that BIM gives, specifically with respect to the limitations currently seen in its application throughout the complete lifecycle of a building, as well as the necessary integration of new technologies such as Artificial Intelligence (AI), which could further augment the capabilities of BIM in the future [2], [3], [6].

1.2 AI in Technological Innovation

AI represents a quickly advancing technological boundary that is increasingly recognized for its large potential to revolutionize the AEC industry, especially when it is effectively and strategically unifies with BIM. The capabilities of AI in the areas of automation, optimization, and predictive analytics are being used to enhance and improve aspects associated with AEC projects, because of that facilitating improved efficiency and usefulness in project execution. Specifically, AI possesses the remarkable ability to automate repetitive tasks that often use valuable time and resources, to predict potential design flaws before they show, and to provide complete data-driven insights that assist interested parties in making informed decisions throughout the project lifecycle [2], [7].

The use of AI with BIM addresses some of the challenges that are linked with the application of BIM technologies in the AEC sector. Advanced AI technologies, which include but are not limited to machine learning algorithms and natural language processing capabilities, have the potential to greatly enhance the use of BIM by significantly improving the accuracy of project predictions, checks to ensure sticking to governmental standards, and optimizing the management of resources to maximize efficiency [8]. This relationship between AI and BIM holds the revolutionary potential to reduce construction timelines, lower overall project costs, and boost the overall outcomes of projects by automating tasks that have traditionally required large labor input and manual supervision [2], although depending of the Level of Development (LOD) of the model it can be challenging to address the amount of data [9].

1.3 Research Objectives and Paper Structure

The aim of this article is to investigate the link between BIM and AI within the AEC industry, with a focus on the role that AI plays in reducing the weaknesses and challenges currently facing BIM applications. This research evaluates AI-driven solutions across the multifaceted stages of AEC projects, covering the stages of design, construction, and management, by analyzing a selection of recent scholarly articles published between the years 2023 and 2024. This academic paper will evaluate the following specific objectives:

1. To perform an evaluation of the current uses of AI within BIM, while at the same time investigating its potential to optimize processes across different phases of AEC projects.
2. To identify and analyze the current limitations of BIM, while looking into how AI can overcome these challenges.
3. To propose a framework designed to enhance the skills of BIM using AI technologies, with the goal of improving both workflow efficiency and overall project results.

To achieve these objectives, the structure of the paper is organized in the following way: First, the methodology section outlines the systematic review process, and the evaluative framework established for both the applications of AI and the barriers of BIM. Following this, the literature review provides an overview of the strengths and advantages of BIM within the AEC industry, which is succeeded by a search of the weaknesses that BIM systems currently encounter. This examination is followed by a discussion of the applications of AI within the AEC sector. In the subsequent sections, the paper shifts into an analysis of the practical applications of AI in BIM throughout the different phases of project implementation. Within the results and discussion part, the potential inherent in the integration of AI with BIM is examined, with a focus on the implementation challenges and potential strategies to overcome them. Additionally, a comparative analysis is shown, contrasting traditional BIM workflows with those that have been enhanced through AI technologies.

The paper ends with a summary of the key findings obtained from this comprehensive investigation, next to suggestions for future research.

2. Methodology

This research used a structured literature review (SLR) approach, which serves as a comprehensive methodological framework aimed at investigating the integration of AI technologies with BIM practices specifically within the realm of the AEC industry. The implementation of a systematic methodology for the review of existing literature not only facilitates a transparent and replicable process but also ensures the validity of the findings by incorporating an array of pertinent studies, consequently minimizing potential bias and enhancing the relevance of the results. This following to methodological rigor is instrumental in guaranteeing that the findings are both reliable and reflective of the most significant and contemporary advancements within the field [10], [11].

The methodological framework employed in this study is composed of five principal stages, as delineated in Figure 1: the initial phase involves defining the research question, followed by the stages of locating pertinent studies, selecting and evaluating those studies, analyzing the findings obtained, and ultimately culminating in a thematic framework analysis designed to derive conclusions. This approach ensures a complete exploration of the role that AI plays in enhancing BIM processes within the AEC sectors.

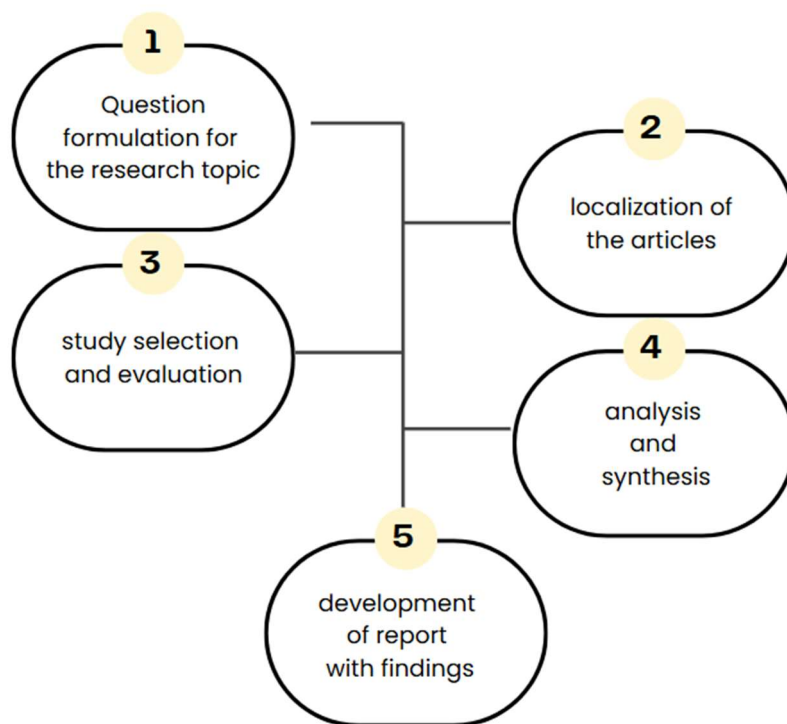


Figure 1: five steps of an SLR, adapted from Denyer & Tranfield (2009).

Step 1: Definition of the Research Guide Question

The initial phase of the methodology entails the process of delineating the research question, as it is shown in figure 2, which is the cornerstone upon which the study is constructed and developed. This phase importance lays the groundwork necessary to establish the main point of the systematic review, ensuring that there is a well-defined scope that facilitates the identification of relevant sources.

Within the context of this investigation, the research question was explained in the following manner: "In what ways can the incorporation of artificial intelligence augment and improve the design and management processes that are inherent within Building Information Modeling (BIM)?" This question specifically connected with the capabilities offered by artificial intelligence and the workflows and barriers associated with BIM, with a concentrated emphasis on design, construction and management phases. The formulation of this question was designed to locate the enhancements that could be made to BIM processes, while delving into the potential that AI technologies possess to mitigate the acknowledged deficiencies that are often found within BIM practices.

The parameters and boundaries of the research question were shaped by the identification of weaknesses and barriers highlighted in the existing body of literature, which included: BIM's flexibility and adaptability constraints, the inefficiencies associated with data management practices, as well as the opportunities that artificial intelligence could provide in terms of fostering more intelligent, automated, and efficient solutions throughout the construction lifecycle [10].

Step 2: Locating Studies

The subsequent phase of the research process entails the selection and evaluation of articles to provide insights and answers to the research question. To carry out a complete and detailed literature search, the Scopus database was judiciously selected and utilized, given its extensive coverage of a wide array of peer-reviewed journal articles, conference proceedings, as well as industry-specific studies that are particularly relevant to the domains of AEC alongside advancements in technology research [10].

To ensure the selection of relevant articles, the following set of inclusion criteria was applied during the review process:

Publication Date: In the context of this study, only those research articles that have been published from the year 2023 onwards were considered. This limitation was implemented to ensure that the literature review remains focused on the most recent advancements and the current state-of-the-art methodologies that are associated with the integration of AI into BIM practices. The search process first resulted in a collection of 446 articles. During this critical phase of evaluation, a total of 239 articles were determined to be unsuitable for inclusion, as they were either not classified as scholarly articles or failed to include content that was published from the year 2023 onwards, thus ensuring the temporal relevance of the selected literature.

Keywords: The comprehensive search for relevant literature was conducted utilizing a curated combination of keywords, which included the terms “BIM” and “AI”. These keywords were required to appear within the title, abstract, or keywords section of each respective article, to improve identification of their relevance in relation to the established research question. In this evaluation, articles that did not incorporate the specific keywords "BIM" and "AI" within their titles, abstracts, or designated keywords were excluded from consideration, resulting in an additional 61 articles being removed from the potential pool of literature to be analyzed.

To facilitate effective management and organization of these articles, they were exported in a CSV format for use with the Zotero, which allowed for systematic organization, efficient reference tracking, and the prevention of any potential duplication of studies within the dataset.

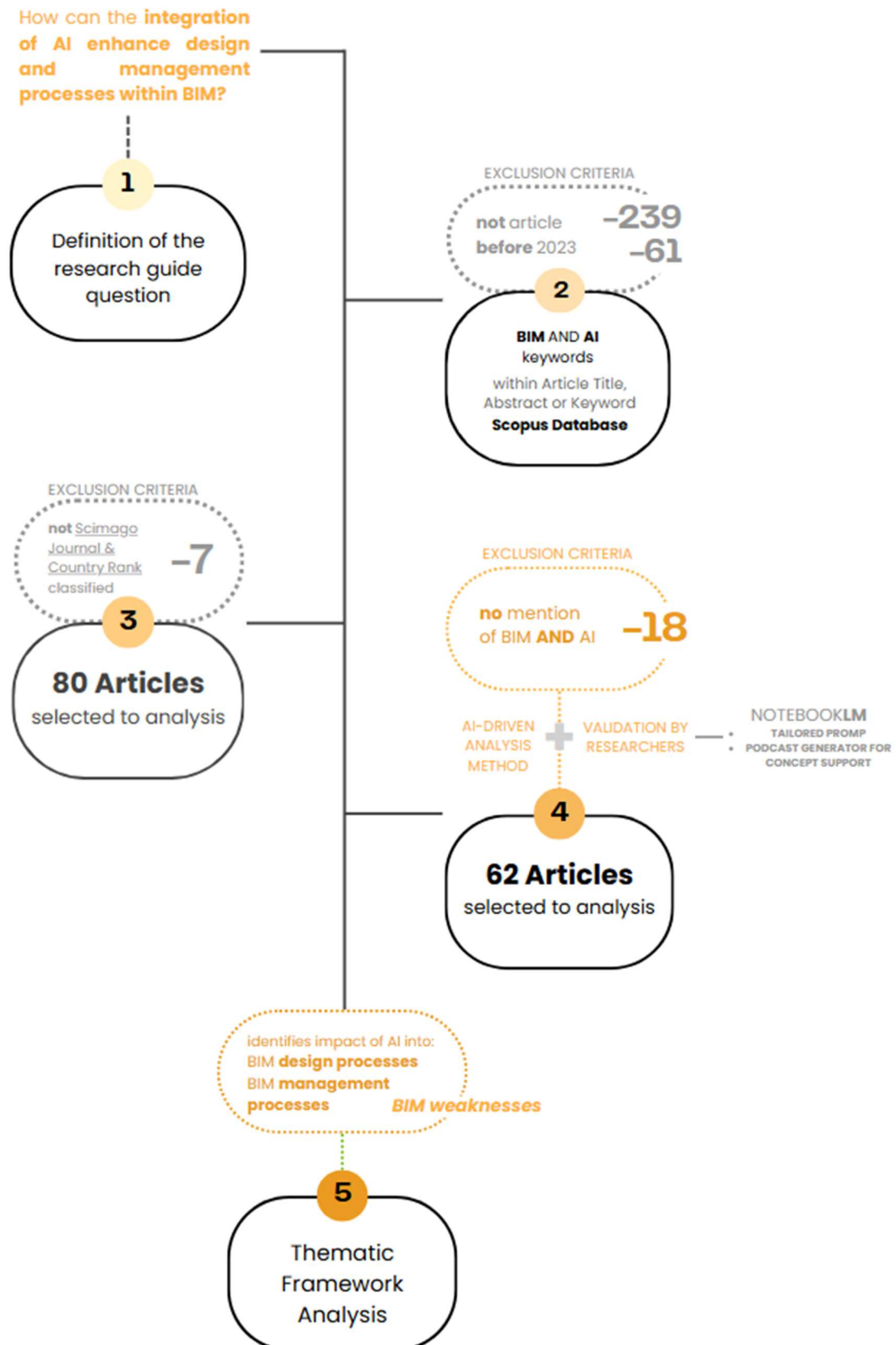


Figure 2: Constrains for articles selection chart (Authors' work).

Step 3: Study Selection and Evaluation

The third step of the methodology is dedicated to the evaluation of the selected articles to ensure that only those publications with relevant information are incorporated into the final analytical synthesis of the research findings. The selection process was divided into multiple distinct and sequential phases, each designed to refine the pool of literature.

Journal Quality Assessment: In the journal quality assessment phase, articles that were published in journals that did not receive classification under the Scimago Journal & Country Rank were excluded from the analysis, thereby ensuring that only those publications from reputable and recognized sources were taken into account, which ultimately led to the exclusion of 7 articles from the final selection.

Step 4: Analysis and Synthesis

Full-Text Screening: During the full-text screening phase, supported by the NotebookLM AI-powered tool, an additional 18 articles were excluded from consideration due to their mention or discussion of the integration of both BIM and AI or AI applications to the AEC industry. Furthermore, the authors utilized the AI-powered podcast generator to enhance the speed and efficiency of their review process, particularly for summarizing and synthesizing key insights, beyond analyzing articles written not in the English language. This tool was also instrumental in simplifying the comprehension of complex articles, enabling a more streamlined approach to refinement. Consequently, a total of 62 articles were retained for comprehensive and detailed analysis.

These 62 articles collectively constituted the foundational basis of the systematic review and were chosen based on a strict set of quality control measures that encompassed aspects such as the peer-review status of the publications, their indexing in recognized databases, and their direct relevance to research focus of this study.

Step 5: Thematic Framework Analysis

In the fifth and final stage of the research methodology, the empirical findings derived from the study were subjected to a thematic framework analysis, which is a systematic approach to data interpretation that yielded a comprehensive and structured overview of the multifaceted ways in which AI exerts its influence on BIM within the intricate design and management

processes that are characteristic of AEC projects. The thematic framework that was developed for this analysis concentrated on three pivotal areas of inquiry **Design, Construction and Management processes**.

In this step, an examination and a synthesis of the 62 articles that were selected for this study were conducted. The articles were analyzed to uncover and identify recurring themes and discernible trends of AI applications, as well as AI applications to BIM weaknesses. This intricate process was executed utilizing thematic framework analysis, which is a qualitative data analysis methodology that identifies patterns spanning a diverse array of studies [12].

The articles were reviewed to identify and summarize the main AI applications used within the AEC sector, with a specific focus on those directly applied to BIM methods. The analysis aimed to build a comprehensive understanding of the current approaches and strategies for employing artificial intelligence, paying particular attention to the challenges of integrating these technologies into BIM practices. This focus highlights how AI can address the inherent weaknesses of traditional BIM methods and implementation. Additionally, the findings shed light on existing gaps in both literature and practice that require further investigation, offering a balanced perspective that recognizes both the strengths and limitations of the current state of AI and BIM integration.

The study concludes by enclosing the notion that the integration of AI not only serves to enhance the current practices employed within the AEC industry but also offers a future-oriented approach with the potential to deeply transform the landscape of this industry [10].

4. Systematic review

4.1 Overview of BIM Strengths in AEC

The foremost advantage BIM possesses is predominantly rooted in its remarkable ability to promote data-centric and integrated project management workflows, which enhance the overall efficiency and effectiveness of construction projects. Importantly, the capacity of BIM to not only generate but also vividly visualize intricate three-dimensional (3D) models significantly enhances the comprehension of stakeholders, thereby fostering a collaborative environment that is essential throughout both the design and construction phases of any project [13], [14], [15]. Furthermore, the robust capabilities of BIM are exemplified in its proficiency in managing extensive data throughout the entire building lifecycle, which not only facilitates transparency but also plays a crucial role in minimizing potential errors that may arise across various project phases [16], [17]. Through the centralization of critical information, BIM effectively cultivates a collaborative environment that is conducive to early conflict detection, which ultimately results in a reduction of design errors and an enhancement of more effective project coordination among all parties involved [18], [19]. The impact of these capabilities has been observed to lead to a significant decrease in both project timelines and overall costs associated with construction [20], [21].

Moreover, the enhanced coordination that occurs between various disciplines constitutes another pivotal advantage of BIM, wherein diverse stakeholders, including architects, engineers, and contractors, are allowed to collaborate seamlessly through the utilization of a unified model that serves as a shared reference point [22], [23]. Additionally, BIM plays an instrumental role in the enhancement of resource management practices by delivering comprehensive and precise estimates concerning quantities and costs, which in turn facilitates superior project budgeting and effectively helps in the avoidance of unnecessary waste [24], [25].

4.2 AI Applications in the AEC Industry

The incorporation of Artificial Intelligence into the AEC industry has created many new opportunities for the optimization of workflows, the enhancement of safety measures, and the overall augmentation of efficiency in BIM processes, thereby revolutionizing traditional practices [26]. A comprehensive review of the literature reveals a vast and diverse array of the main artificial intelligence applications, as shown in different graphs in figures 3, 4, and 5,

that effectively address pivotal challenges encountered within the AEC sector, encompassing a spectrum that ranges from generative design methodologies to predictive maintenance systems.

AI Application Type	Authors (Year)	Description of Applications
Generative Design and Optimization	Wang et al. (2024), He et al. (2025), Wang et al. (2023), Wang, L. et al. (2023)	Generative design, Predictive analytics for structural design, AI for building layout generation, Optimization for transportation hubs
Augmented Reality (AR) Applications	Fawad et al. (2024), Mohamed et al. (2024)	AR for bridge health monitoring, AR applications in AEC for enhanced monitoring and visualization
Deep Learning for Safety and Monitoring	Dzeng et al. (2024), Dobrucali et al. (2024), Dzeng, R.-J. et al. (2024), Fawad et al. (2024)	Scaffolding safety monitoring, Emerging technologies impact on safety, Construction site risk management
Predictive Maintenance	Mehraban et al. (2024), Lin, C. et al. (2023), Lin, Y. et al. (2023), Moyano et al. (2024)	Predictive safety and maintenance analytics, Predictive risk management for heritage buildings, Predictive maintenance using ML
Digital Twins	Ospina-Bohórquez et al. (2023), Shlash Mohammad et al. (2024), Croce et al. (2023)	Digital Twin for construction monitoring, Scan-to-BIM technologies, Monitoring of wind farms
Real-Time Data Analysis	Wang et al. (2024), Wang et al. (2023), Lin, C. et al. (2023), Croce et al. (2023)	Real-time data analysis, AI for construction site data analysis
Workflow Automation	Fernandes et al. (2024), Costa et al. (2023), Almaz et al. (2024)	GPT-powered assistant, early warning systems for workspace safety, automation in design practices
AI for Energy Optimization	Mehraban et al. (2024), Chen et al. (2024), Croce et al. (2023), Moyano et al. (2024)	Energy optimization, deep learning for mitigating planning, energy production prediction in PV integration
Safety Risk Assessment	Lin et al. (2023), Hosseini Gourabpasi & Nik-Bakht (2024), Pishdad & Onungwa (2024)	Safety risk assessments using AI, automated fault detection in construction
Modular and Sustainable Design	Alzara et al. (2023), Standard & Kucukayan (2024), Redondo et al. (2023), Almaz et al. (2024)	Genetic algorithm-based cost optimization, modular construction with AI
Natural Language Processing (NLP)	Jang et al. (2024)	Automated detailing using natural language processing, natural language assistance for architectural detailing
Internet of Things (IoT) Integration	Al-Rasheed et al. (2024), Koumou & Isafiade (2024), Zhao, Y. et al. (2023)	IoT integration for enhanced monitoring, Equipment monitoring, Smart integration with AI
Digital Heritage and Scan-to-BIM	Carpio De Los Pinos et al. (2024), Croce et al. (2023), Moyano et al. (2024)	Classification of heritage buildings, segmentation, historic structure conservation
Collaboration and Communication	Fernandes et al. (2024), Mohamed et al. (2024), Lin, C. et al. (2023)	Collaboration improvements via AI, Visionary constructs, Extended reality for improved teamwork

Figure 3: Description of 14 AI applications.table (Authors's work).

AI-powered generative design tools, exemplified by innovative frameworks that incorporate Generative Adversarial Networks (GANs), have markedly diminished the temporal demands associated with design iterations by autonomously producing many design alternatives, thereby facilitating a more efficient exploration of various design possibilities [27], [28]. This sophisticated approach empowers designers to investigate an extensive array of alternatives with remarkable efficiency, ultimately resulting in a more informed and judicious decision-making process [14], [29], [30], [31]. Furthermore, AI-enhanced BIM frameworks have been adeptly employed for the purposes of multi-objective optimization, which aids in the identification of the most economically viable and energy-efficient design solutions, particularly in the context of intricate and multifaceted projects [32], [33], [34].

AI has proven to be a crucial element in the optimization of resource allocation, which has significantly empowered project managers to deploy both human labor and material resources with a higher degree of efficiency throughout the various stages of construction projects [35]. For example, specific AI applications, particularly those based on genetic algorithms, have been strategically utilized to optimize not only cost management but also the distribution of resources, resulting in financial savings and the generation of more predictable and reliable project outcomes [25], [32], [36]. Furthermore, the advent of AI-driven safety monitoring systems has revolutionized the concept of safety on construction sites, as advanced deep learning-based systems have been implemented to detect potential hazards proactively, which in turn has contributed to a significant reduction in risks and the prevention of accidents that could lead to serious injuries or fatalities [21], [23], [37], [38].

The application of AI for real-time data analysis has facilitated a more dynamic and responsive approach to decision-making processes within AEC projects, allowing for an unprecedented level of adaptability in addressing emerging challenges. AI tools that are seamlessly integrated with advanced technologies such as drones and Internet of Things (IoT) devices provide stakeholders with the most current and relevant data, thereby enabling them to make informed decisions with a degree of agility that is unattainable when relying on traditional BIM methodologies [34], [39], [40], [41], [42]. In addition to these advancements, the realms of collaboration and communication have been significantly enhanced through the implementation of AI-based systems, including those powered by Generative Pre-trained Transformers (GPT), which have greatly improved interactions among stakeholders by

delivering instantaneous feedback and bolstering efforts toward effective coordination [24], [43], [44].

Predictive maintenance represents a significant application of artificial intelligence, which comprehensively addresses the inherent deficiencies associated with the proactive capabilities traditionally found within BIM frameworks as they pertain to facility management practices. Through the utilization of sophisticated machine learning algorithms, it becomes feasible to accurately anticipate potential system failures, thereby enabling building operators to engage in preemptive maintenance activities prior to the occurrence of substantial breakdowns, which could otherwise lead to detrimental operational disruptions [45], [46], [47]. The efficacy of these predictive capabilities is particularly pronounced when applied to the management of intricate building systems, such as heating, ventilation, and air conditioning (HVAC) systems and structural systems wherein artificial intelligence algorithms are adept at forecasting maintenance requirements by analyzing sensor data alongside historical performance metrics [18], [48], [49].

The issue of data security remains a persistent challenge in the widespread adoption of BIM technologies across various sectors. In this context, artificial intelligence, especially when integrated with blockchain technology, has emerged as a pivotal force in safeguarding the integrity and security of the data that is exchanged among the diverse stakeholders involved in building projects [17], [48], [50]. Furthermore, artificial intelligence enhances the efficiency of workflow automation processes, thereby substantially diminishing the necessity for manual data entry and frequent documentation updates, which in turn not only amplifies overall productivity but also significantly reduces the likelihood of human error, a factor that often undermines operational efficiency [22], [24], [51].

AI Application Type	Number of papers mentioning
Generative Design and Optimization	5
Augmented Reality (AR) Applications	3
Deep Learning for Safety and Monitoring	5
Predictive Maintenance	5
Digital Twins	4
Real-Time Data Analysis	5
Workflow Automation	3
AI for Energy Optimization	4
Safety Risk Assessment	5
Modular and Sustainable Design	4
Natural Language Processing (NLP)	2
Internet of Things (IoT) Integration	5
Digital Heritage and Scan-to-BIM	4
Collaboration and Communication	3

Figure 4: Number of mentions of AI application (Author's work)

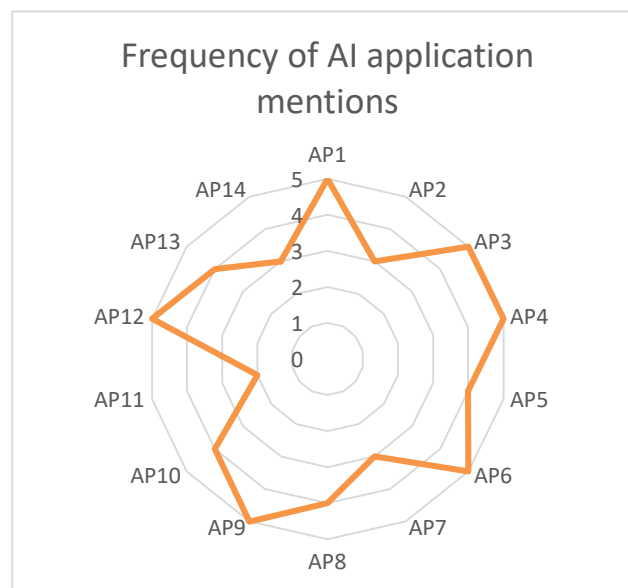


Figure 5: Number of AI application' mentions radar chart (Authors' work)

4.3 Applications of AI in BIM Phases

4.3.1 AI in the Design Phase

AI within the framework of BIM during the design phase has transformed the methodologies employed [52], [53], as it has significantly optimized spatial arrangements, enhanced collaborative efforts among stakeholders, and ensured adherence to sustainability principles throughout the design and construction processes. The process of generative design, which is underpinned by sophisticated AI models such as GANs, empowers designers to swiftly and

proficiently explore and analyze several architectural configurations, facilitating a more innovative and efficient design process. In the research conducted by Wang et al. (2024), the authors effectively harnessed the capabilities of GANs for the automated generation of spatial layouts, which not only optimized the functionality and aesthetic appeal of the designs but also substantially minimized the necessity for manual intervention in the design workflow [14]. Jang et al. (2024) contributed to this advancement by introducing an innovative natural language processing (NLP)-based tool named NADIA, which is capable of converting verbal descriptions into comprehensive and detailed architectural layouts, thereby significantly reducing the burden of manual labor and expediting the overall design process [44]. Furthermore, Yavan et al. (2024) employed AI methodologies to enhance the optimization of truss designs within BIM models, resulting in considerable savings in material usage while simultaneously improving the structural integrity of the constructions involved [54].

The role of AI is progressively becoming more pivotal in fostering sustainability within the design sector. In a notable study, Mahasneh and Almigbel (2024) successfully integrated occupant behavior analysis into BIM frameworks through the application of AI techniques, culminating in a remarkable 20% reduction in discrepancies between projected and actual energy consumption figures, thus promoting a closer alignment of energy usage predictions and real-world outcomes [55]. Additionally, Al-Rasheed et al. (2024) effectively utilized AI-driven life-cycle assessments integrated within BIM systems to optimize the selection of materials, thereby achieving key sustainability objectives through a significant reduction of environmental impacts by an impressive 15% [34]. Mehraban et al. (2024) emphasized the application of AI-enhanced BIM models in simulating the energy performance of buildings situated in extreme climatic conditions, which led to the development of optimized HVAC designs that achieved a notable reduction in overall energy usage by 25% [18]. In a similar vein, Abouelaziz and Jouane (2024) capitalized on the synergy between photogrammetry and AI technologies to optimize the integration of photovoltaic systems within building designs, thereby supporting broader initiatives aimed at promoting renewable energy sources [56]. Khan et al. implemented a framework to automate energy consumption analysis with a result of 13% energy consumption improvement, lowering CO₂ building emissions [57].

The collaborative efforts among various stakeholders within the AEC sector have seen a remarkable enhancement, a phenomenon that can be attributed to the innovative integration of AI-BIM integration. In their research, Fernandes et al. (2024) introduced an advanced assistant powered by GPT technology, a tool designed to furnish users with immediate and insightful feedback concerning the intricacies of building information modeling (BIM) models, thereby significantly mitigating the potential for miscommunication that often arises

between the diverse teams responsible for design and construction processes [24]. Furthermore, Takashi et al. (2023) implemented augmented reality (AR) tools augmented by artificial intelligence to facilitate the dynamic visualization of structural components, a method that not only promotes more effective communication between design teams and stakeholders present on-site but also ensures that these interactions are particularly fruitful during the preliminary phases of project development [50]. Additionally, Koumou and Isafiade (2024) utilized virtual reality (VR) simulations, which were seamlessly integrated with artificial intelligence technologies, to create an interactive platform allowing stakeholders to engage with three-dimensional BIM models, thus significantly improving their level of engagement and comprehension regarding complex architectural designs [43]. Lastly, Lee et al. (2024) showcased the pivotal role that artificial intelligence plays in the formulation of design solutions that not only acknowledge but actively accommodate individuals with physical disabilities, thereby fostering a sense of inclusivity through the development of adaptive spatial models that cater to a broader range of user needs [13]. Figure 6 highlights several AI applications referenced in the design phase.

Authors (Year)	AI Application	Description & Impact
Wang et al. (2024)	GAN for Spatial Layout Generation	Automated spatial layout generation optimized functionality and aesthetics, reduced manual intervention.
Jang et al. (2024)	NADIA (NLP-based Tool)	Converts verbal descriptions to architectural layouts, reducing manual labor and speeding up design process.
Yavan et al. (2024)	AI for Truss Design Optimization	Optimized truss designs in BIM, achieved material savings, and improved structural integrity.
Mahasneh & Almigbel (2024)	Occupant Behavior Integration	AI integrated occupant behavior into BIM, reducing energy discrepancies by 20%.
Al-Rasheed et al. (2024)	AI-Driven Life-Cycle Assessment	Optimized material selection for sustainability, reduced environmental impacts by 15%.
Mehraban et al. (2024)	AI for Building Energy Performance	Simulated building energy performance in extreme climates, optimized HVAC designs, and reduced energy by 25%.
Abouelaziz & Jouane (2024)	AI + Photogrammetry for PV	Optimized photovoltaic integration in buildings to support renewable energy initiatives.
Fernandes et al. (2024)	GPT-Powered Assistant	Provides instant feedback on BIM models, reducing miscommunication between design and construction teams.
Takashi et al. (2023)	AI-Enhanced AR Tools	Visualized structural elements, enhancing communication between design and on-site teams during early stages.
Koumou & Isafiade (2024)	Immersive VR + AI Simulations	Improved stakeholder engagement with 3D BIM models, enhancing understanding of complex designs.
Lee et al. (2024)	Adaptive Spatial Models for Accessibility	Created inclusive designs to accommodate individuals with physical disabilities through AI models.

Figure 6: Impact of AI applications in the Design Phase

4.3.2 AI in the Construction Phase

The phase of construction within AEC projects experiences significant advantages through the integration of AI into BIM as illustrated in (figure 7), which not only enhances overall productivity but also plays a crucial role in ensuring the safety of operations on-site, while simultaneously optimizing the allocation and utilization of available resources [58]. The advent of digital twins has emerged as a pivotal development, establishing them as indispensable instruments for the continuous monitoring and assessment of construction sites. Ospina-Bohórquez et al. (2023) effectively employed digital twins in the oversight and evaluation of wind farm construction activities, achieving a remarkable reduction of 25% in discrepancies identified between the as-designed specifications and the actual as-built models [20]. Similarly, Takashi et al. (2023) illustrated the significant impact that digital twins had in

the management of bridge construction projects, whereby their implementation markedly enhanced communication channels between site teams and project managers, thereby facilitating a more cohesive operational framework [21]. Furthermore, Lin et al. (2023) explored the application of reinforcement learning methodologies within the context of large-diameter tunnel construction, which enabled the optimization of the distribution of both material and human resources, ultimately resulting in a noteworthy reduction of resource wastage by 30% [39].

The paramount concern for safety within the construction industry has led to the development and implementation of advanced AI-driven tools designed specifically to mitigate potential risks and hazards. In a notable study, Dzeng et al. (2024) introduced an innovative AI-powered scaffolding deficiency detection system that seamlessly integrates deep learning techniques with augmented reality applications, achieving an impressive detection rate of 95% for unsafe conditions and consequently contributing to a significant reduction in the overall risk of accidents occurring on construction sites [37]. In a similar vein, Dobrucali et al. (2024) harnessed the capabilities of AI-driven predictive safety models within BIM frameworks to identify activities characterized by high risk, which facilitated proactive intervention strategies that ultimately led to an 18% decrease in the frequency of site accidents [21]. Additionally, Kumar et al. (2024) employed AI technologies to ensure rigorous compliance with established safety regulations, effectively automating the process of on-site safety inspections and subsequently minimizing the necessity for manual intervention by human operators [19].

AI has played a pivotal role in the optimization of resources throughout the construction process, significantly enhancing various operational aspects. In a groundbreaking study conducted by Alzara et al. (2023), the researchers successfully implemented genetic algorithms within BIM frameworks, thereby refining project scheduling mechanisms, which remarkably culminated in a 15% enhancement in both cost management and overall project efficiency, as evidenced by their findings [32]. In a complementary investigation, Takashi et al. (2023) introduced an innovative AI-enhanced system specifically designed for the inspection of rebar arrangements, which not only automated the inspection process but also achieved a remarkable reduction in labor requirements by 65%, all the while ensuring that precision standards were rigorously maintained [36]. Furthermore, Fawad et al. (2024) explored the synergistic application of AR in conjunction with AI technologies for bridge health monitoring, which enabled the seamless real-time integration of inspection data with BIM models, ultimately resulting in significantly improved predictive maintenance strategies [33].

Moreover, automation and robotics are progressively advancing their footprint within the construction industry, demonstrating considerable potential for enhancing operational efficiency. Shlash Mohammad et al. (2024) underscored the promising utilization of AI-driven robotic systems for conducting dynamic simulations in both educational and construction contexts, which yielded substantial productivity gains by accurately simulating human tasks directly on construction sites [47]. In a similar vein, Lin (2023) developed an advanced chatbot that was seamlessly integrated into the BIM framework, specifically designed to assist construction managers by facilitating real-time data retrieval [36], thereby empowering them to make prompt and well-informed decisions, which ultimately resulted in a marked improvement in communication efficiency across project teams [22]. Additionally, Chen et al. (2024) conducted an in-depth exploration into the realm of automated fire risk assessments employing computer vision technologies alongside AI, ensuring that building blueprints consistently adhered to established safety codes while concurrently mitigating risks throughout the construction phase [29].

Material and energy management strategies implemented during the construction phase have significantly reaped numerous advantages as a direct result of the integration of artificial intelligence technologies [59]. In a notable study conducted by Abouelaziz and Jouane in the year 2024, the researchers effectively employed a combination of photogrammetry techniques in conjunction with artificial intelligence methodologies within the context of BIM to meticulously optimize various energy-related components associated with construction projects, which notably included the strategic placement of photovoltaic panels to enhance energy efficiency [56]. Furthermore, Pishdad and Onungwa, also in the year 2024, adeptly harnessed the capabilities of artificial intelligence to streamline the processes of cost estimation and cost control, which ultimately resulted in a more precise prediction of material costs and a significant reduction in the occurrence of budget overruns that frequently plague construction endeavors [60]. Additionally, the research conducted by Shao et al. in 2023 demonstrated the successful application of artificial intelligence technologies aimed at optimizing the energy consumption of lighting systems specifically within library buildings during the construction phase, which led to a remarkable reduction in overall energy consumption by an impressive 18% [61].

AI Application	Authors (Year)	Impact/Results
Digital twins for wind farm construction monitoring	Ospina-Bohórquez et al. (2023)	Reduced discrepancies by 25%
Digital twins for bridge construction management	Takashi et al. (2023)	Improved communication between teams and managers
Reinforcement learning for tunnel construction	Lin et al. (2023)	Reduced resource wastage by 30%
AI-powered scaffolding deficiency detection system	Dzeng et al. (2024)	95% detection rate for unsafe conditions
AI-driven predictive safety models for high-risk	Dobrucali et al. (2024)	18% reduction in site accidents
AI for safety compliance and on-site checks	Kumar et al. (2024)	Automated safety checks, reduced manual intervention
Genetic algorithms for project scheduling in BIM	Alzara et al. (2023)	15% improvement in cost control and efficiency
AI-enhanced rebar arrangement inspection	Takashi et al. (2023)	Reduced labor requirements by 65%
AR and AI for bridge health monitoring	Fawad et al. (2024)	Enhanced predictive maintenance
AI-driven robots for dynamic simulations	Shlash Mohammad et al. (2024)	Significant productivity improvements
Chatbot for real-time data retrieval in construction	Lin (2023)	Enhanced communication efficiency
Automated fire risk assessment using computer	Chen et al. (2024)	Ensured blueprints met safety codes, reduced risks
Photogrammetry and AI for energy optimization in BIM	Abouelaziz and Jouane (2024)	Optimized energy-related components, PV panel
5D BIM and AI for cost estimation and control	Pishdad and Onungwa (2024)	Accurate material cost prediction, minimized budget
AI for energy optimization in library lighting systems	Shao et al. (2023)	Reduced energy consumption by 18%

Figure 7: Impact of AI applications in Construction (Authors's work).

4.3.3 AI in the Management Phase

The management phase within AEC projects experiences significant advantages through the integration of AI into BIM as illustrated in (figure 8). In the management phase of building operations, the integration of AI with BIM is predominantly centered around the optimization of energy consumption, the implementation of predictive maintenance protocols, and the proficient administration of various building systems, all of which are critical to enhancing operational efficiency [62], [63], [64]. In a notable study conducted by Costa et al. (2023), the researchers innovated the Ventilation Early Warning System (VEWS), a sophisticated system that synergizes the IoT with AI to enable the dynamic adjustment of HVAC operations in accordance with fluctuating occupancy patterns, which ultimately culminated in a remarkable

30% reduction in overall energy consumption [51]. In a similar vein, Mehraban et al. (2024) illustrated the efficacy of AI-driven simulations aimed at assessing energy performance in buildings situated within extreme climatic conditions, which not only optimized energy strategies but also yielded significant financial benefits, resulting in cost savings that could reach as high as 25% [18].

In addition, predictive maintenance emerges as a pivotal application area for AI-BIM integration throughout the operational lifecycle of buildings. In a comprehensive proposal put forth by Hosseini Gourabpasi and Nik-Bakht (2024), an ontology-driven Artificial Intelligence framework was introduced, which seamlessly integrates with Building Information Modeling to facilitate the automation of fault detection within HVAC systems, leading to a substantial reduction in downtime and the associated financial implications, ultimately achieving a commendable 15% decrease in costs [45]. Moreover, Talib and Crook (2023) underscored the significant role that Artificial Intelligence plays in the management of power consumption within smart building environments, elucidating how AI's capacity to dynamically modulate energy usage can effectively optimize overall power consumption, thereby facilitating savings of approximately 20% [46]. Additionally, Zhao et al. (2023) presented a comprehensive integration of Artificial Intelligence with IoT systems specifically designed for the predictive maintenance of construction machinery, which served to extend the operational lifespan of such machinery by accurately predicting potential failures and implementing timely mitigative measures [22].

The application of artificial intelligence within the operational phase of building management significantly encompasses the intricate management of both building performance, sustainability initiatives and safety [63], [65]. Alavi et al. (2024) conducted a comprehensive study that adeptly illustrated how the incorporation of digital twin technology, when synergistically integrated with advanced artificial intelligence systems, facilitated the continuous and real-time monitoring of healthcare facilities, which in turn optimized energy consumption while simultaneously enhancing the comfort levels of patients within those facilities [46]. In a similar vein, artificial intelligence augments the adaptability of various building systems by establishing a connection between Building Information Modeling (BIM) frameworks and IoT devices, thereby empowering facility managers to effectively align operational requirements with live data streams, leading to a substantial enhancement of

overall building performance metrics [34], [66]. Furthermore, Ospina-Bohórquez et al. (2023) accentuated the significant role of digital twins in facilitating the monitoring of renewable energy sources that are seamlessly integrated into the operational frameworks of buildings, ultimately contributing to a reduction in overall operational costs associated with building management [20].

Authors (Year)	AI Application	Impact/Results
Costa et al. (2023)	Ventilation Early Warning System (VEWS)	30% reduction in energy use
Mehraban et al. (2024)	Energy Performance Optimization in Extreme Climates	25% cost savings
Lin et al. (2023)	AI and IoT Integration for Energy Management	Energy efficiency and occupant comfort improvements
Hosseini Gourabpasi & Nik-Bakht (2024)	Ontology-driven AI for HVAC Fault Detection	15% reduction in downtime
Talib & Crook (2023)	AI for Power Management in Smart Buildings	20% savings in power consumption
Zhao et al. (2023)	AI & IoT Integration for Predictive Maintenance	Extended machinery life, predictive maintenance
Alavi et al. (2024)	Digital Twins for Real-time Monitoring in Healthcare	Optimized energy usage, improved patient comfort
Al-Rasheed et al. (2024)	AI-Enabled Adaptability for Building Systems	Improved building performance, real-time adjustments
Ospina-Bohórquez et al. (2023)	Digital Twins for Renewable Energy Monitoring	Reduced operational costs

Figure 8: AI applications to Management Phase (Authors's work).

5. Results and Discussion

To initiate the discussion, it was essential to draw on insights from earlier studies, including those in which one of this paper's authors participated. The 18 BIM implementation barriers [67] identified previously have now been cross-referenced with the 14 AI applications within the AEC sector identified in this research . These 18 barriers are illustrated in Figure 9.

Barrier	Description
B01	Lack of BIM adoption definition methods/workflows
B02	Lack of BIM Uses definitions and objectives
B03	Lack of project parties' collaboration
B04	Undefined security, legal liability, and responsibility
B05	Management/contractual BIM processes (e.g., BEP)
B06	Undefined related business standards for BIM adoption
B07	Cost of BIM tools (e.g., software, hardware, etc.)
B08	Cost of expertise and training support
B09	Risk of return on investment and financial profits
B10	Unclearity of financial benefits and economic risks
B11	Industry resistance and difficulty to change processes
B12	Client's resistance and lack of market demand
B13	Lack of BIM knowledge, awareness, and research
B14	Lack of BIM experience, experts, and trainings
B15	Lack of IT infrastructure (software, hardware, etc.)
B16	Lack of mandate regulations and policy support
B17	Lack of time for full BIM adoption and skill developing
B18	Lack of proof for efficiency, and potential of BIM

Figure 9: BIM implementation barriers (Adapted from Altamimi et al.).

5.1 Transformative Potential of AI-BIM Integration

The remarkable capability of AI to automate the process of design generation, optimize resource allocation, and significantly enhance predictive maintenance functionalities positions it as an invaluable instrument through which many of the longstanding limitations inherent in conventional BIM can be effectively surmounted. The generative design capabilities elucidated by Wang et al. (2024) facilitate an accelerated iteration process of spatial configurations, thereby augmenting both the efficiency and the creative potential inherent in the design phase [14]. In a similar vein, Jang et al. (2024) underscored the pivotal function of NLP tools, e.g. NADIA, in simplifying the detailing phase of projects, which not only alleviates manual workloads but also significantly enhances the overall efficiency of the workflow [44].

The potential for transformative change is not confined solely to the design phase; it also encompasses the operational stage, wherein the predictive maintenance capabilities offered by AI have markedly revolutionized the management of facilities. For instance, Costa et al. (2023) engineered an AI-enhanced HVAC system that utilizes real-time occupancy data to

optimize energy consumption effectively, resulting in a notable improvement in operational efficiency [51]. The advantages of employing AI for energy optimization have been further evidenced by the findings of Mehraban et al. (2024), which revealed that machine learning-enhanced HVAC systems can yield cost savings of up to 25% [18]. These advanced capabilities illustrate the scalability and adaptability of AI-enhanced BIM, thereby enabling a more responsive approach to decision-making that is firmly grounded in data-driven insights.

Regardless of these advantages, recent investigations into the barriers associated with BIM have brought to light obstacles that must be addressed to facilitate the effective integration of AI within BIM frameworks (figure 9). Among the most critical challenges identified is the lack of standardized methodologies and workflows for the adoption of BIM, which impedes the consistent implementation of these practices across various projects (B01) [67]. The absence of clearly defined standards contributes to discrepancies and complications in harmonizing BIM practices with established business processes and regulatory mandates. In this context, AI possesses the potential to bridge these gaps by offering adaptive solutions and fostering standardization through the utilization of machine learning models, which are capable of learning from and adjusting to the best practices derived from existing datasets [34].

5.2 Challenges and Strategies for Implementation

Although AI possesses considerable potential to overcome the weaknesses associated with BIM, there exist numerous challenges that continue to obstruct its extensive adoption within the AEC industry. One of the most significant barriers that has been identified pertains to the substantial costs associated with the utilization of BIM tools, which encompass a broad range of expenses related to both software licenses and hardware procurement (B07) [67]. This particular challenge becomes increasingly pronounced when one considers the necessity for AI integration, as the deployment of advanced computational resources is frequently required to effectively execute complex machine learning algorithms and models. Furthermore, the financial burden associated with acquiring the requisite expertise and training support represents another formidable obstacle, as many firms find themselves grappling with the difficulty of locating and financing the essential skills needed for the successful implementation of BIM methodologies (B08) [67].

Moreover, it is imperative to acknowledge that cultural and organizational barriers significantly contribute to the sluggish pace of BIM adoption across the industry landscape.

The reluctance of the industry to embrace change, coupled with a conspicuous lack of market demand for solutions driven by BIM technology, has been identified as critical impediments that hinder progress (B11, B12) [67]. While AI possesses transformative capabilities, it necessitates a profound cultural shift within organizations to ensure that its myriad benefits can be fully actualized and harnessed. One strategy that has been proposed to effectively navigate and surmount these challenges involves the cultivation of a learning-oriented culture within organizations, which would actively promote upskilling in various digital technologies. Implementing training programs that are specifically tailored to focus on the effective utilization of BIM and AI tools can significantly contribute to mitigating resistance, as these programs would equip teams with the requisite knowledge and competencies needed to proficiently operate these sophisticated systems [23].

Additionally, it is crucial to highlight that concerns regarding data security represent a substantial challenge, particularly in the context of integrating AI with BIM frameworks (B04) [67]. The practice of sharing sensitive project-related data across a multitude of AI platforms inherently amplifies the risk of potential data breaches and unauthorized access. In light of these concerns, the adoption of blockchain technology has been proposed as a viable solution to bolster data integrity and security, particularly within cloud-based AI-BIM platforms, as evidenced by the research conducted by He et al. (2025) [17]. Another strategic approach to addressing these issues involves the implementation of comprehensive regulatory frameworks designed to delineate clear data-sharing protocols, which would serve to ensure that stringent data privacy and security standards are consistently met and upheld.

5.3 Mapping AI Strengths to BIM Weaknesses

The comparative analysis of the strengths inherent in AI juxtaposed with the weaknesses associated with BIM elucidates the potential of AI to proficiently mitigate the obstacles that have been identified in recent scholarly research as shown in (figure 10). A particularly notable deficiency within BIM pertains to the absence of a well-defined framework for adoption, compounded by the ambiguous delineation of roles and responsibilities that are to be assumed by various stakeholders involved in the project (B01, B02) [67]. Through the utilization of predictive analytics and sophisticated machine learning models, AI possesses the capability to standardize these procedural frameworks by recommending optimized workflows derived from an analysis of historical data, thereby ensuring a comprehensive understanding of responsibilities among all parties engaged in the project [14], [17].

In addition to the aforementioned issues, another critical shortcoming of BIM is inherently linked to management and contractual complexities, which notably include the absence of clearly articulated BEPs alongside the lack of well-defined business standards (B05, B06) [67]. The deployment of AI tools, such as the GPT-powered assistant recently introduced by Fernandes et al. (2024), holds promise in assisting with the definition and development of BEPs by meticulously analyzing analogous past projects and formulating templates that are congruent with prevailing industry standards [24]. This innovative approach markedly alleviates the burdensome workload typically faced by project managers while simultaneously ensuring that BIM processes are effectively implemented throughout the entire lifecycle of the project.

Moreover, the financial implications associated with BIM tools, coupled with the substantial training requirements, have been emphasized as considerable barriers to widespread adoption (B07, B08) [67]. By leveraging AI-driven automation, it becomes feasible to significantly reduce these financial burdens through a decrease in the necessity for manual input, while also enhancing the efficacy of training initiatives via the creation of personalized learning pathways that are generated by advanced AI models. Such AI-based systems are adept at identifying the specific skill gaps that may exist among individual team members and subsequently recommending targeted training programs, thus effectively addressing the prevalent lack of skills and awareness that often hinders the adoption of BIM methodologies (B14) [67].

AI Application to BIM Barriers and Weaknesses Matrix															
-	AP1	AP2	AP3	AP4	AP5	AP6	AP7	AP8	AP9	AP10	AP11	AP12	AP13	AP14	Σ
B01	1						1								2
B02											1				1
B03					1									1	2
B04													1		1
B05					1		1							1	3
B06												1			1
B07										1					1
B08		1													1
B09				1											1
B10	1					1									2
B11			1						1						2
B12					1										1
B13		1									1				2
B14							1								1
B15				1											1
B16															0
B17						1									1
B18								1							1
W01												1			1
W02										1					1
W03			1												1
W04							1			1					2
W05					1								1		2
W06									1						1
W07	1							1							2
W08		1												1	2

Figure 10: AI application to BIM barriers.and weaknesses.

5.4 Comparative Analysis: Traditional vs. AI-Enhanced BIM Workflows

The incorporation of AI into BIM signifies a profound shift away from conventional BIM methodologies, particularly with respect to aspects such as operational efficiency, adaptability to changing conditions, and the effective utilization of data resources. As delineated in the accompanying scholarly research, traditional BIM methodologies encounter a myriad of obstacles, including the absence of well-defined adoption standards, exorbitant costs associated with implementation, and a pronounced resistance to transformative changes within the industry (B01, B07, B11) [67]. These impediments frequently result in operational inefficiencies, wherein stakeholders involved in projects grapple with the challenge of articulating clear processes, delineating responsibilities, and establishing expected outcomes in a coherent manner.

In stark contrast to these traditional methodologies, workflows enhanced by AI present a more sophisticated, data-centric, and automated paradigm for BIM processes. For example, it is

noteworthy that traditional approaches necessitate considerable manual intervention in the creation of BIM models while simultaneously ensuring adherence to regulatory requirements. The utilization of AI-driven tools, particularly those innovated by Dzung et al. (2024), facilitates the automation of safety compliance assessments through the application of deep learning techniques, which in turn diminishes the reliance on manual labor and significantly enhances the precision of the outputs generated [37]. Furthermore, the conventional dependence on static design frameworks is effectively alleviated by the generative capabilities inherent in AI technology, which empowers rapid iterations and optimizations tailored to specific project constraints, as compellingly illustrated by the research conducted by Wang et al. (2024) [14].

Another significant distinction that merits attention pertains to the realm of operational efficiency, which serves as a critical factor in assessing the overall performance of building management systems. It has been observed that traditional Building Information Modeling (BIM) frameworks frequently encounter considerable challenges when it comes to the meticulous and effective monitoring of energy performance metrics and the ongoing maintenance of various equipment, both of which are essential components in the endeavor to optimize the operational capabilities of buildings [67]. In contrast, the integration of AI into BIM processes, as exemplified by the innovative predictive maintenance algorithms elucidated by researchers Hosseini Gourabpasi and Nik-Bakht (2024), facilitates the anticipation of potential failures and the proactive scheduling of maintenance activities, thereby contributing to the prolongation of asset lifespans and the minimization of operational expenditures [46].

In conclusion, while it is evident that traditional BIM workflows are proficient in generating a digital representation of tangible structures, the advent of AI-enhanced BIM represents a significant advancement by transforming the models into intelligent entities that possess the capability to learn from extensive datasets, foresee future outcomes, and automate the decision-making processes. This transformative shift not only effectively addresses numerous obstacles that have been identified in the context of BIM adoption but also paves the way for the emergence of novel possibilities that promote more efficient and economically viable construction methodologies.

6. Conclusion summary

The incorporation of AI into the framework of BIM has unequivocally exhibited an capacity to revolutionize operational processes throughout the multifaceted landscape of the AEC sector, thereby significantly augmenting levels of productivity, enhancing adaptability in various contexts, and promoting operational efficiency in an increasingly complex environment. This study underscored the myriad ways in which applications of AI effectively tackle numerous intrinsic limitations associated with BIM, which encompass persistent challenges related to standardization practices, overall cost management, and the effective utilization of data in diverse scenarios. The implementation of AI generative design tools has facilitated the automation of spatial configurations, thereby expediting design workflows while concurrently minimizing the potential for human errors that often occur during the intricate process of design detailing. Furthermore, AI-driven collaborative tools, such as the GPT-powered BIM assistant, have effectively demonstrated the potential for a reduction in communication gaps, which in turn fosters enhanced stakeholder engagement while simultaneously mitigating the occurrence of delays in project timelines [20].

From a broader operational standpoint, the advent of AI-enabled predictive maintenance strategies and advanced energy management systems has yielded promising outcomes, significantly enhancing overall building performance metrics while simultaneously driving down operational costs as evidenced by the research findings of Costa et al. (2023) and Mehraban et al. (2024). These innovative AI applications play a crucial role in directly addressing the weaknesses inherent in BIM, particularly those associated with elevated operational expenses and inefficiencies in maintenance practices, by optimizing the utilization of resources and providing proactive maintenance schedules that are both timely and effective [37], [39]. Moreover, the utilization of predictive algorithms specifically designed for risk assessment and energy optimization, as illustrated by the research conducted by Lin et al. (2023) and the collaborative work of Hosseini Gourabpasi and Nik-Bakht (2024), further exemplifies the role that AI plays in bridging the operational gaps that exist within the BIM framework [32], [43].

This investigation also delineated the various strengths inherent in AI and how they correlate with and subsequently address the existing deficiencies found within BIM. The advent of AI-driven tools specifically designed for safety management, exemplified by the pioneering work conducted by Dzung et al. (2024), effectively tackled BIM's significant limitation in

consistently upholding safety standards through the implementation of automated safety inspections and evaluations, which in turn significantly reduces the likelihood of human oversight and error in these critical assessments [25]. Furthermore, the remarkable capacity of AI to predict and optimize resource allocation, as evidenced by the findings of Alzara et al. (2023), successfully surmounted one of the most pressing challenges faced by BIM in relation to the efficient and effective planning of resources necessary for construction projects [33]. Additionally, by integrating blockchain technology to enhance data security measures, as proposed by He et al. (2025), AI possesses the substantial potential to alleviate BIM's vulnerabilities with respect to data privacy and protection, thereby transforming it into a highly robust and reliable tool for the secure management and handling of sensitive data [46].

A pivotal contribution of this comprehensive study lies in the thorough identification and elaboration of strategic approaches designed to effectively overcome the numerous barriers associated with the adoption of BIM through the utilization of AI technologies. The process of adopting BIM is fraught with significant obstacles, which include, but are not limited to, the absence of standardized procedures, exorbitant implementation costs, and pressing concerns surrounding data security, all of which have been meticulously highlighted in the accompanying document that details the weaknesses inherent in BIM (B01, B07, B04) [67]. By strategically leveraging advanced AI technologies, such as machine learning for the purpose of predictive analytics, in conjunction with blockchain technology aimed at ensuring data integrity, the AEC industry stands to comprehensively address these existing weaknesses in a far more efficient and effective manner. Not only does AI facilitate the reduction of costs associated with the implementation and utilization of BIM by automating various processes and thereby minimizing the necessity for human intervention, but it also actively cultivates a culture of collaborative innovation through the adoption of immersive technologies including Augmented Reality (AR) and Virtual Reality (VR) applications, which significantly enhance the overall effectiveness of BIM practices [22], [23], [68].

The potential inherent in the integration of AI with BIM for the AEC industry is extraordinarily vast and profound in its implications. The empirical findings derived from this research unequivocally demonstrate that AI technologies not only serve to significantly enhance the pre-existing capabilities of BIM but also effectively tackle and mitigate critical barriers that have historically impeded progress, such as various management complexities, contractual challenges, and the exorbitant operational costs that are often associated with traditional practices. The automation, optimization, and predictive capabilities afforded by AI

stand poised to effectively bridge the existing chasm between the traditional limitations that have long constrained the AEC industry and the modern expectations that are increasingly demanded in today's fast-evolving landscape. As we look toward the future, it is fundamentally essential that the key to fully realizing the comprehensive potential of AI-BIM integration resides in the standardization of AI applications across the sector, the fostering of comprehensive industry-wide training programs, and the implementation of effective and robust regulatory frameworks specifically designed to ensure data security. These decisive steps will not only assure that AI is harnessed to enhance the efficiency of BIM practices but will also serve to make these practices significantly more accessible and versatile for the diverse array of stakeholders that operate across the expansive spectrum of the AEC industry [18], [20], [46].

In conclusion, while the advent of BIM has already instigated a plethora of significant improvements in project management and design methodologies within the AEC industry, the integration of AI represents a leap forward that has the potential to revolutionize the field. It becomes imperative the pursuit of research and development efforts in the realm of AI technologies that can support scalable, sustainable, and secure BIM practices moving forward. By addressing and rectifying the inherent weaknesses of BIM through the application of AI, as underscored in this comprehensive study, the AEC industry stands to advance toward a future that is characterized by unprecedented levels of innovation, operational efficiency, and sustainability—ultimately paving the way for the realization of smarter and more resilient infrastructure development outcomes.

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