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Automating Construction Scheduling with AI: A Comparative Study of BIM and Non-BIM Approaches

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ABSTRACT: Construction scheduling is a complex and critical component of project planning with substantial financial implications. Effective scheduling enhances project efficiency by controlling costs, allocating resources, and reducing durations. Manual scheduling is common, but this method can be time-consuming and prone to errors. Automation in construction scheduling has been evolving since the early 1980s, with recent advances focusing on the transformative potential of Artificial Intelligence (AI). The industry-standard approach to automated scheduling is centred around Building Information Modeling (BIM), prompting researchers to explore integrations of AI with BIM software. BIM models serve as excellent data sources for AI to create construction schedules, since BIM models store a wide array of data such as spatial relationships, construction sequencing logic, building element information and material properties. Recently, AI has evolved to extract valuable insights from language-based documents and floor plans, enabling new approaches to construction scheduling that extend beyond traditional BIM reliance. Methods such as deep reinforcement learning, Natural Language Processing (NLP), and Large Language Models (LLMs) show promise, although these techniques remain relatively novel and underexplored in construction. This paper reviews AI methods for automated construction scheduling, comparing the benefits of BIM-based and non-BIM-based approaches across different stages of the scheduling process. The different stages of the scheduling process analyzed are schedule preparation, schedule analysis and optimization, schedule updates, and schedule control. Overall, both BIM-based and non-BIM approaches show potential for AI driven automation in construction scheduling, each presenting unique benefits and challenges. This study highlights these aspects and suggests directions for future research.

1. INTRODUCTION

1.1 Artificial Intelligence

Historically reliant on manual and labor-intensive processes, the construction industry has increasingly recognized the potential of AI to enhance efficiency, reduce errors, and optimize outcomes (Abioye et al., 2021). There are many applications of AI in the construction industry, including cost estimation, contract management, supply chain management, health and safety, site monitoring, and scheduling (Abioye et al., 2021). Among the various applications of AI in construction, scheduling remains a critical yet challenging aspect. Effective scheduling ensures timely project delivery, cost control, and resource optimization, which are pivotal to project success (Yao et al., 2024).

A common definition for Artificial Intelligence (AI) is the ability of technology or computers to perform tasks that are often performed by intelligent beings, particularly humans. The term began in the early 1950s, coinciding with the development of the first AI program to automatically solve complex mathematical theorems (Chen & Ying, 2022). In the 1980s, the development of AI shifted towards Machine Learning (ML). ML is a subset of AI which focuses on learning from the surrounding environment. ML techniques lend themselves to more complex tasks, such as pattern recognition or computer vision (Naqa & Murphy, 2015). In the late 2000s and early 2010s, Deep Learning (DL) became a focal point in the AI world, with efficient learning procedure for generative models, DL could solve even more complex problems leading to the AI emergence of modern times (Chen & Ying, 2022).

1.2 Automation in Construction Scheduling

Beginning in the 1980s, knowledge-based systems, such as PLANEX, were one of the first technologies used to attempt to automate construction scheduling (Hendrickson et al., 1987, Zozaya-Gorostiza et al., 1990). This technology combined a knowledge base, operators and context in a combined BIM and CPM scheduling predecessor. It built the schedule semi-automatically by using pre-defined “if-then” rules as part of an “expert system. Case-based reasoning was another early approach, using previous situations and data to determine what should be done in a current situation (Faghihs et al., 2015). Model-based approaches began in the 1990s, starting with component-based CAD models as the data source for algorithms to develop construction schedules (Faghihs et al., 2015).

In the 1990s, genetic algorithms (GAs) were introduced to optimize construction schedules by simulating natural selection, improving time, cost, and resource allocation (Faghihs et al., 2015). The 2000s saw the emergence of neural networks, which improved scheduling predictions using historical data, though they required substantial computational resources and large datasets (Faghihs et al., 2015). In the 2010s, the integration of Building Information Modeling (BIM) with scheduling processes enabled 4D simulations, linking timelines with 3D models for improved visualization and tracking (Faghihs et al., 2015). More recently, adaptive systems using Internet of Things (IoT), computer vision and 3D scanning have been developed to dynamically adjust schedules in response to site conditions (Turkan et al., 2012). Large language models (LLMs) like ChatGPT are now being explored for automating early-stage scheduling tasks, while emerging AI reasoning models such as OpenAI’s o1/o3 and DeepSeek’s DeepThink offer potential for human-like decision-making based on project data (Prieto et al., 2023).

Manual construction scheduling methods rely heavily on expert judgment, static planning tools, and manual updates, making them time-consuming and prone to errors (Hatami et al., 2021). The introduction of automation, particularly through AI, offers significant improvements by substituting machines for humans in the mundane work of creating early schedule drafts, and by enabling dynamic scheduling, real-time adjustments, and data-driven decision-making (Prieto et al., 2023). Building Information Modeling (BIM) has been a cornerstone for integrating AI into construction scheduling, serving as a data source that facilitates schedule automation (Rane, 2023). However, recent advancements in AI techniques, including Natural Language Processing (NLP), Deep Reinforcement Learning (DRL), and Large Language Models (LLMs), have opened avenues for non-BIM-based scheduling approaches (Rane, 2023; Singh, 2023).

1.3 Scope and Objective

The objective of this paper is to explore emerging BIM-based and non-BIM-based AI approaches for automating construction scheduling. The applicability of methods across the different stages of the scheduling lifecycle, including schedule preparation, analysis, updates, and control is explored. By analyzing the strengths and limitations of each approach, the paper provides an overview of their potential impact on overall project outcomes, as well as promising directions for related future research.

2. TRADITIONAL CONSTRUCTION SCHEDULING

2.1 Phases of a Construction Schedule

Traditional construction scheduling is a process that involves several interdependent phases, including schedule preparation, schedule analysis and optimization, schedule updates, and schedule control. These concepts are introduced in most construction management and construction scheduling textbooks, including Hendrickson et al, 2024. Schedule preparation includes defining project scope, identifying major activities, and establishing task dependencies. Schedulers rely on issued-for-construction (IFC) drawings, specifications, and contract documents, which contain essential information on spatial relationships, resources, and sequencing (Al-Sinan et al., 2024). Professional judgment is critical to interpret these documents and determine the tasks needed for execution.

In the analysis and optimization phase, schedulers assess feasibility and refine the plan to improve resource use and meet deadlines. Traditional techniques support basic checks but lack the dynamic optimization capabilities of modern algorithms, often relying on static logic that falls short in complex scenarios (Hatami et al., 2021). Schedule updates are required throughout project execution to reflect progress and changes. This often involves manually gathering data from daily logs, site reports, and stakeholder feedback. For large or fast-paced projects, manual updates are time-consuming and labour-intensive (Singh, 2023).

Schedule control ensures the project stays on track by comparing actual progress to the baseline plan and identifying deviations. Tools like Oracle Primavera P6 and Microsoft Project support this phase but depend heavily on static data, limiting their ability to respond to real-time changes (Rane, 2023; Singh, 2023).

2.2 Manual Scheduling Challenges and Limitations

Traditional construction scheduling faces several challenges, especially in complex or large-scale projects. One key issue is its time-consuming nature. Creating and maintaining schedules requires substantial effort, particularly when integrating data from multiple sources like drawings, specifications, and stakeholder inputs. This manual process increases the risk of errors, leading to inefficiencies and timeline inaccuracies (Wu et al., 2023; Prieto et al., 2023). Manual methods also lack optimization capabilities. Schedulers often rely on intuition, making it difficult to determine optimal task sequences or resource allocations (Singh, 2023). New project schedules are frequently adapted from past projects, sometimes inheriting outdated logic. Whether starting fresh or from templates, manual approaches struggle to evaluate multiple scenarios or simulate optimal outcomes efficiently, often resulting in suboptimal plans (Hatami et al., 2021).

Expert judgment introduces further variability. Schedule quality can vary significantly depending on the scheduler's experience, especially when fast, reactive planning is needed in dynamic environments (Hatami et al., 2021). Data fragmentation adds another layer of complexity. Project information is spread across diverse sources such as drawings, BIM models, work-breakdown-structures (WBSs), contract documents, and site reports, making integration into a cohesive schedule difficult (Singh, 2023). These limitations highlight the need for advanced methodologies capable of handling real-time complexity. Artificial Intelligence (AI) shows promise in addressing these issues by automating data synthesis, enhancing decision-making, and improving schedule optimization (Yao et al., 2024; Hatami et al., 2021).

3. AI TECHNOLOGIES FOR AUTOMATING CONSTRUCTION SCHEDULING

3.1 Relevant AI Technologies

3.1.1 Deep Reinforcement Learning (DRL)

Deep Reinforcement Learning (DRL) is a type of machine learning that trains algorithms to make sequential decisions by interacting with an environment and learning from trial-and-error feedback. DRL employs a reward-feedback mechanism, optimizing actions to achieve a defined objective, such as minimizing construction duration or resource use. This approach is especially suitable for complex, dynamic problems like construction scheduling, where real-time adjustments are necessary (Yao et al., 2024). DRL is especially valuable in the schedule analysis and optimization stage. During schedule analysis and optimization, DRL algorithms evaluate dependencies, constraints, and resource allocation to generate optimal task sequences.

DRL has wide-ranging applications across the scheduling lifecycle, specifically in the schedule analysis and optimization stage. During schedule analysis and optimization, DRL algorithms evaluate dependencies, constraints, and resource allocation to generate optimal task sequences. For example, Yao et al. (2024) demonstrated DRL's capability to reduce project durations by adjusting task dependencies dynamically. In this study, a schedule created manually by an experienced project scheduler was 336 hours in duration, while a DRL model was able to organize the schedule so that it was 251 hours in duration, a significant 25.2% reduction in the scheduled project duration. When performing schedule updates, DRL can quickly adapt to disruptions like labor shortages or delayed material deliveries by rescheduling activities based on updated conditions.

However, the study noted that DRL requires substantial computation and extensive hyperparameter tuning, making training time-consuming. These challenges persist even when optimizing only project duration and would intensify in multi-objective scenarios. Additionally, the model assumes ideal conditions—no delays, uninterrupted workflow, and immediate resource availability—which may limit its adaptability to unexpected constraints in real-world projects. DRL is a powerful optimization tool but lacks the ability to generate construction tasks or estimate durations or required resources, requiring integration with other AI models or systems to create a comprehensive scheduling framework.

3.1.2 Natural Language Processing (NLP)

Natural Language Processing (NLP) is an AI technology that focuses on enabling computers to understand, interpret, and generate human language. NLP is particularly effective in processing unstructured textual data, such as contracts, specifications, and daily site reports, making it a valuable tool in construction scheduling (Prieto et al., 2023).

During the schedule preparation phase, NLP can automate the extraction of critical details from project documents, such as activity descriptions, dependencies, and milestones, reducing manual effort and improving accuracy (Singh, 2023). For instance, it can analyze contracts and technical specifications to identify essential tasks, significantly accelerating the creation of preliminary schedules (Prieto et al., 2023). NLP can learn company specific construction knowledge from past schedules, and generate new schedules based on that information (Singh, 2023). NLP can also play a role in updating schedules by parsing daily progress reports and site logs to identify completed tasks or delays, enabling dynamic timeline adjustments (Al-Sinan et al., 2024). In schedule analysis, NLP can validate task dependencies and identify inconsistencies in schedules, ensuring logical accuracy and minimizing errors (Rane, 2023).

While NLPs demonstrate a lot of potential, it is not a tool designed with construction in mind. As a result, models often struggle with domain-specific knowledge, often making incorrect assumptions such as adding unnecessary demolition or omitting critical steps like door framing. Additionally, NLP lack real-time data access, making it unreliable for cost estimation and resource planning. These inconsistent outputs and difficulty handling complex dependencies suggest that NLP-based scheduling still requires human validation and further industry-specific training (Prieto et al., 2023).

3.1.3 Large Language Models (LLMs)

Large Language Models (LLMs), such as OpenAI's ChatGPT, extend the capabilities of NLP by offering advanced language understanding and generation. LLMs are trained on vast datasets, enabling them to interpret complex textual inputs, generate task sequences, and suggest project timelines. LLMs have shown potential in schedule preparation, where they can interpret unstructured project descriptions to create logical sequences of activities (Prieto et al., 2023). For example, project managers can use LLMs to draft an initial schedule based on provided details, which can then be refined through iterative interactions. Although their integration into schedule control is still emerging, LLMs can assist by providing textual explanations of deviations and suggesting corrective actions. However, their performance depends on high-quality input data and iterative refinement to ensure accurate outputs (Singh, 2023).

For simple educational purposes, LLMs such as Microsoft's CoPilot, can generate simple CPM schedules in the form of a verbal specification with reasonably good logic. They can also add a list of project risks related to the type of project but not the specific project. Other AI tools can be used to convert this output into input suitable for commercial CPM scheduling software. However, according to Pallagani et al. (2024), LLMs face several limitations in automated planning and scheduling (APS). They often hallucinate non-existent tools, overuse certain functions, and struggle with scaling in complex planning. Additionally, LLMs lack adaptability in symbolic problem-solving, making them unreliable for precise action sequencing. Furthermore, their spatial reasoning is weak, limiting their ability to construct accurate world models.

3.1.4 Other Machine Learning (ML) Techniques

Other machine learning techniques, including genetic algorithms (GAs) and deep learning networks, offer additional methods for improving construction scheduling. GAs simulate natural selection to optimize solutions for task sequencing and resource allocation, making them highly effective in schedule analysis and optimization (Rane, 2023). For example, GAs can explore multiple scheduling scenarios to identify the most efficient allocation of resources under complex constraints (Hatami et al., 2021).

Deep learning networks, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) models, are valuable in schedule preparation and schedule updates. They analyze historical data to predict activity durations, resource requirements, and potential risks. For instance, LSTM models can identify trends in past projects to inform the scheduling of similar activities, improving the accuracy of initial plans (Hatami et al., 2021).

Ensemble approaches that combine multiple ML techniques offer comprehensive solutions for construction scheduling. For example, an integrated system might use NLP for data extraction, GAs for optimization, and RNNs for predictive analysis, ensuring robust performance across the scheduling lifecycle. However, these methods require high-quality training data and substantial computational resources, which may limit their applicability to resource-constrained projects (Al-Sinan et al., 2024).

They also require expert human knowledge and judgment to evaluate their logic, completeness, absence of hallucinations and inconsistencies emerging from random seeding. As well, a human ultimately must take responsibility and be held accountable for the accuracy and utility of the schedule. A master scheduler and estimator should always remain in the loop, in the opinions of the authors of this paper.

3.2 Summary of Applications

Table 1 includes a summary of the AI technologies applicable to automating construction scheduling. The table highlights each technology's applicability to the four distinct phases of the schedule lifecycle.

Table 1: Summary of Non-BIM AI Scheduling Technology Applications

Technology	Schedule Preparation	Schedule Analysis and Optimization	Schedule Updates	Schedule Control	Limitations	Sources
Deep Reinforcement Learning (DRL)		Evaluate dependencies, constraints, and resource allocation to optimize task sequences.	Adapt to disruptions by rescheduling activities based on updated conditions.		High computational requirements, no task generation or resource estimation	Yao et al., 2024; Rane, 2023; Hatami et al., 2021

Natural Language Processing (NLP)	Automate the extraction of critical details from project documents, such as activity descriptions, dependencies, and milestones. Create new schedules based on previous schedules.		Search daily progress reports and site logs to identify completed tasks or delays, enabling dynamic timeline adjustments.		Lack of domain-specific understanding, no real-time data access, inconsistent outputs	Singh, 2023; Prieto et al., 2023; Rane, 2023
Large Language Models (LLMs)	Interpret unstructured project descriptions to create logical sequences of activities.			Explain deviations and suggest corrective actions.	AI hallucinations (potential inaccuracies), scaling challenges, dependence on high-quality input	Prieto et al., 2023; Singh, 2023
Genetic Algorithms (GAs)		Explore multiple scheduling scenarios to identify the most efficient allocation of resources under complex constraints			High computational requirements, cannot generate tasks (serves as an optimization tool)	Hatami et al., 2021
Deep Learning Networks	Analyze historical data to predict activity durations, resource requirements, and potential risks				High computational requirements, AI hallucinations (potential inaccuracies), requires high quality input	Hatami et al., 2021

3.3 Industry Examples

3.3.1 ALICE Technologies

ALICE is an AI-powered construction scheduling platform that has been successfully applied in real-world projects. Marketed as an "AI construction optioneering" tool, it simulates schedule scenarios based on project-specific requirements to help planners explore trade-offs in duration, cost, and resource utilization. Users can adjust inputs such as crew size, sequencing logic, and productivity rates to evaluate a range of feasible outcomes. A key strength of ALICE is its ability to integrate with industry-standard scheduling and BIM platforms, including Primavera P6, Microsoft Project, and BIM 360, allowing it to operate using either an existing schedule or a BIM model as its data source (ALICE Technologies, 2025). ALICE employs a constraint-based generative AI system that relies on a parametric engine, rather than traditional machine learning. (ALICE Technologies, 2025).

Several general contractors have successfully implemented ALICE on large-scale infrastructure and high-rise projects. Reported outcomes include reductions in project duration by up to 17%, labour cost savings of 14%, and equipment cost savings of 12% (ALICE Technologies, 2025). ALICE improves both the schedule analysis and control phases by enabling project teams to make data-informed decisions throughout the construction lifecycle. During schedule analysis and optimization, it allows users to generate and compare multiple schedule options based on cost, time, and resource constraints, helping project managers identify the most efficient sequencing strategies for their specific goals. For schedule control, ALICE offers real-time “optioneering” capabilities, allowing teams to simulate the impact of potential disruptions, such as material delays or labor shortages, and adjust schedules by selecting alternative paths or reallocating resources before issues escalate (ALICE Technologies, 2025).

3.3.2 Togal.AI

Togal.AI is an AI platform designed to streamline quantity takeoff and cost estimating, supporting the schedule preparation phase of construction projects. Schedule preparation often relies on accurate quantity data, productivity rates, and resource forecasts to define task durations and sequencing. Traditionally, this process is time-consuming and error-prone, requiring estimators to manually interpret IFC drawings and extract quantities for scheduling inputs. Togal.AI addresses this challenge by using deep learning networks and Natural Language Processing (NLP) to automatically analyze drawings and technical specifications. The system identifies and classifies construction elements and calculates quantities in real time, dramatically reducing the time required to generate schedule-ready estimates (Togal.AI, 2025).

The platform's integration with ChatGPT enhances usability by allowing estimators to extract scope information and generate reports using natural language queries, making use of the advantages of LLMs (Togal.AI, 2025). While Togal.AI does not produce schedules directly, it supports the schedule preparation phase by delivering structured data to estimate task durations and resource needs. As deep learning and NLP technologies advance, tools like Togal.AI show how AI can enhance not only cost estimation but also the early development of construction schedules by supplying foundational logic and planning data.

4. BIM VS. NON-BIM COMPARISON

4.1 BIM-Based Applications

BIM-based systems thrive on structured data that integrates geometric, spatial, and attribute information into centralized models. These data-rich environments make use of 4D BIM Simulation Platforms (e.g., Autodesk Navisworks and Bentley Synchro), which can link time with 3D models. This enables stakeholders to detect potential conflicts, visualize progress, and simulate scenarios for better planning and communication (Wu et al., 2023). Genetic Algorithms (GAs) leverage BIM's structured nature to iteratively refine resource allocations and task sequencing, achieving higher accuracy in scheduling outcomes (Rane, 2023).

BIM models are typically not primarily developed for the purpose of construction scheduling, they are created to support a wide range of functions such as clash detection, cost estimation, logistics planning, and facility management (Wu et al., 2020; García de Soto et al., 2017). The structured and information-rich nature of BIM provides a foundation for multiple downstream applications, one of which can be scheduling (Hatami et al., 2021). However, scheduling is often a secondary function that emerges once a BIM model is in place for other purposes. For example, 4D BIM tools were initially developed to visualize project sequencing and detect spatial conflicts, but they have since been leveraged to integrate scheduling techniques such as Tabu-search algorithms to optimize project timelines (García de Soto et al., 2017).

Deep Learning Networks (e.g., RNNs and LSTMs) enhance BIM-based scheduling by predicting activity durations and risks based on historical patterns combined with structured project data. These networks facilitate decision-making by integrating learned insights with BIM's attribute-rich information (Hatami et al., 2021). Deep Reinforcement Learning (DRL) is particularly effective in BIM environments where structured constraints, such as activity sequences and spatial relationships, are available. DRL uses these constraints to optimize schedules dynamically and respond to changes while staying within the BIM-defined parameters (Yao et al., 2024). Additionally, Natural Language Processing (NLP) plays a role in BIM environments by analyzing metadata embedded in BIM models and related documentation, extracting project constraints, or identifying inconsistencies in schedules directly from textual annotations (Singh, 2023).

BIM-based approaches face challenges such as the significant upfront cost and technical expertise required to create and maintain detailed models, particularly at high Levels of Development (LOD). Additionally, BIM models may exclude external factors like weather, supply chain disruptions, or site-specific conditions, limiting adaptability (Hatami et al., 2021). Interoperability between different BIM platforms also poses difficulties, as integrating data across tools can introduce inefficiencies (Rane, 2023).

4.2 Non-BIM Based Applications

Non-BIM approaches are well-suited for projects lacking comprehensive BIM models or dealing primarily with unstructured data. Large Language Models (LLMs) extend NLP capabilities, generating preliminary schedules from textual descriptions and refining them based on user feedback (Liu et al., 2023). Natural Language Processing (NLP) also excels in non-BIM contexts, extracting insights from contracts, specifications, and progress reports to automate scheduling and validation tasks. For example, NLP algorithms can identify dependencies and constraints directly from textual inputs, bypassing the need for structured data (Al-Sinan et al., 2024). Deep Learning Networks in non-BIM environments rely on unstructured historical data to predict activity durations and resource needs, making them particularly effective in data-rich but model-deficient scenarios (Hatami et al., 2021).

These approaches, while flexible and adaptable, also face challenges. The reliance on unstructured data introduces risks related to data quality and inconsistencies, which can lead to flawed schedules or inaccurate analyses (Abioye et al., 2021). Additionally, integrating AI tools with existing project management platforms is often complicated due to a lack of standardized protocols for data exchange (Singh, 2023).

4.3 Comparison

The suitability of AI technologies for BIM or non-BIM contexts depends on their reliance on structured data, adaptability to unstructured inputs, and ability to integrate with project workflows. Figure 1 includes a Venn diagram that categorizes the technologies discussed in this study based on their applicability to BIM or non-BIM based scheduling automation approaches.

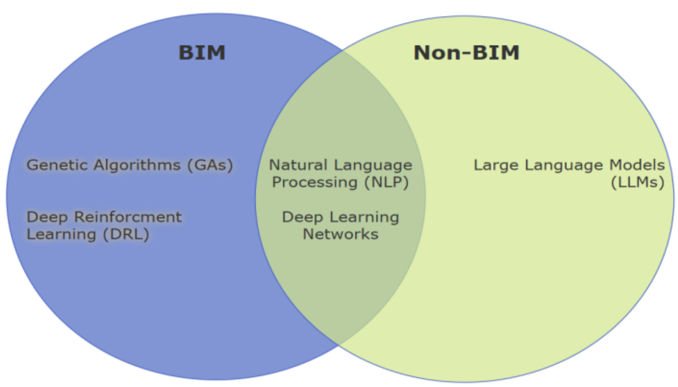

Figure 1: Venn Diagram Comparing BIM and Non-BIM Applicable Technologies

5. CONCLUSION

5.1 Implications for the Construction Industry

AI-driven scheduling holds significant promise for the construction industry. These technologies automate time-consuming tasks like schedule generation and resource allocation, reducing human error and improving the reliability and efficiency of project planning (Singh, 2023; Rane, 2023; Hatami et al., 2021). By easing the reliance on domain expertise, AI allows less experienced managers to develop viable initial schedules, helping to mitigate delays and promote standardized practices across projects (Yao et al., 2024).

However, challenges remain. Issues such as data interoperability, algorithmic bias, and the need for ongoing model training must be addressed for AI to deliver consistent value (Abioye et al., 2021; Rane, 2023). Modern non-BIM approaches like Large Language Models (LLMs) can process unstructured data more easily but tend to struggle with spatial reasoning and construction-specific logic, often due to their training on general datasets. Data privacy is another major concern. Construction projects involve sensitive financial, contractual, and proprietary information. Since LLMs typically rely on cloud-based processing, they pose potential risks related to data breaches, unauthorized access, and regulatory compliance.

Despite these limitations, AI-driven tools can bridge the gap between structured and unstructured project data, enabling a more comprehensive understanding of scheduling needs and constraints. The growing number of AI-enabled platforms, such as ALICE and Togal.AI signals a broader industry shift toward AI-supported scheduling at all project stages. This capacity has the potential to enhance decision-making by providing stakeholders with a clearer picture of project dynamics (Rane, 2023). While integrating AI with BIM amplifies these benefits by synthesizing BIM's structured model data with contextual insights from unstructured sources, AI scheduling systems can also operate independently of BIM. This allows project managers to potentially efficiently create automated schedules without the significant effort and cost required to develop a detailed BIM model, making advanced scheduling tools accessible to a wider range of projects and organizations (Yao et al., 2024).

While AI-driven scheduling offers efficiency and automation benefits, it also introduces concerns regarding user engagement and responsibility. Traditional manual scheduling forces project managers and planners to deeply engage with the intricacies of a project, including task dependencies and resource requirements. When AI automates these tasks, there is a risk that project teams may lose this familiarity. AI-generated schedules introduce questions of accountability—if an error occurs due to an AI-recommended sequencing or resource allocation, it is unclear whether responsibility lies with the project manager, the AI system, or the developers of the model. To mitigate these risks, AI scheduling tools should be designed to support, rather than replace, human expertise, incorporating features that allow project managers to review, modify, and validate AI-generated schedules before implementation. This ensures that while AI enhances efficiency, human decision-makers retain control and accountability over project outcomes.

5.2 Future Directions

Future research should prioritize the development of hybrid scheduling models that integrate the strengths of BIM-based and non-BIM-based approaches. Combining structured BIM data with insights derived from unstructured sources could unlock new possibilities for real-time schedule optimization and adaptability (Rane, 2023). Efforts to enhance data interoperability between BIM platforms and AI tools are critical to achieving seamless integration and widespread adoption (Singh, 2023).

Advancing AI techniques, such as refining Deep Reinforcement Learning (DRL) algorithms and exploring multi-objective optimization methods, will further improve the predictive accuracy and efficiency of automated scheduling systems. For example, implementing Double DQN and Rainbow DQN models can enable more sophisticated learning mechanisms tailored to construction-specific challenges (Yao et al., 2024). Additionally, investments in creating large, construction-specific datasets will be crucial for training AI models that accurately reflect the complexities of construction projects (Hatami et al., 2021). Collaboration between academia, technology developers, and industry stakeholders is essential to ensure that AI solutions address practical constraints while aligning with industry standards and workflows (Abioye et al., 2021). By addressing these areas, the construction industry can fully harness the potential of AI-driven automated scheduling to reduce delays, optimize resource allocation, and deliver projects more efficiently, ultimately fostering a more competitive and innovative sector.

Based on a review of the literature discussed in this study, we find that while AI-driven scheduling offers significant potential, its effectiveness depends on addressing data operability and adaptability challenges. Rather than viewing BIM-based and non-BIM-based approaches as competing methodologies, we believe their combination presents the most promising path forward. Future developments should prioritize solutions that improve, rather than replace, human expertise, ensuring that AI-driven scheduling aligns with real-world construction workflows and project needs.

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