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Comparative Analysis of Manual Vs AI-Assisted Project Scheduling and Cost Estimation in Construction Management

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Abstract: Construction industry is increasingly becoming digitalized but most residential projects are still being done using manual ways of project scheduling and cost estimation which is usually time consuming, inaccurate and subject to human error. This paper will provide a full comparative literature review of the hand-assisted and AI-assisted methods used in construction management and how they enhance the accuracy of the planning process, cost estimation, and resource optimization. The Python-based software application is created with the graphic user interface (GUI) to help the design of residential buildings safe and compliant with all the codes and to incorporate project scheduling and cost estimation features. The methodology is based on a hybrid that integrates traditional planning methods with AI-based models relying on machine learning and predictive analytics, both on real and simulated project data. The comparative evaluation is done using key performance indicators that include time accuracy, cost deviation, and efficiency of resource utilization. The suggested AI-based model will help to improve the accuracy of estimations, reduce delays, and optimize the use of resources in comparison with the manual approach. It is expected that the results will prove that AI-based solutions can enhance efficiency, reliability, and scalability in construction project management and facilitate informed decision-making and encourage the use of intelligent systems in the construction industry.

Keywords: Artificial Intelligence, Construction Management, Project Scheduling, Cost Estimation, Machine Learning, Predictive Analytics, Resource Optimization, GUI-based Software, Residential Construction, Digital Transformation

1.Introduction

Construction industry is a cornerstone of economic expansion and development of infrastructure, but it still faces the same issues of project scheduling, cost estimation, and managing resources. The Gantt charts, Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) are traditional manual techniques that have been long used in planning and execution in residential construction projects. Although such techniques offer a systematic approach, they tend to be time consuming, highly reliant on human knowledge and are prone to errors because of the changing project conditions. This often leads to project delays, cost increase, and poor resource utilization [Sharma et al., 2023].

Over the past years, the evolution of artificial intelligence (AI) and digital technologies have impacted the construction industry greatly as they have brought new options in terms of project management. Machine learning and predictive analytics as AI methods allow making decisions based on data, analysing past project data and pointing out patterns to make better forecasts. These methods have proven to have the ability to increase the accuracy of schedules, minimize uncertainties and streamline cost estimation procedures. It has been demonstrated that AI-based models can be effective compared to traditional estimation techniques, as they offer real-time insights and adaptive features [Guo et al., 2025].

Furthermore, the combination of computational devices and software systems have assisted in automating intricate engineering activities such as structural design and project planning. Python-based systems and graphical user interface (GUI) applications are also finding more applications to simplify processes in the architectural and engineering profession, allowing them to design safe and code-compliant residential buildings efficiently. More sophisticated simulation and modelling also lead to improved visualization and performance analysis of construction projects and thus enhance the overall efficiency in planning [Lee et al., 2025].

The capacity of AI to optimize resources and manage risks is another important issue with AI adoption in construction management. Multi-variable AI-assisted systems have the ability to break down several variables associated with a project at once (like labour availability, cost of materials, and environmental conditions) to produce optimal schedules and cost estimates. This results in better resources allocation, less wastage, and lesser risks of the project. Furthermore, AI applications can be constantly trained with new information, which makes them more accurate and flexible in contrast to the fixed manual methods [Kumar et al., 2024].

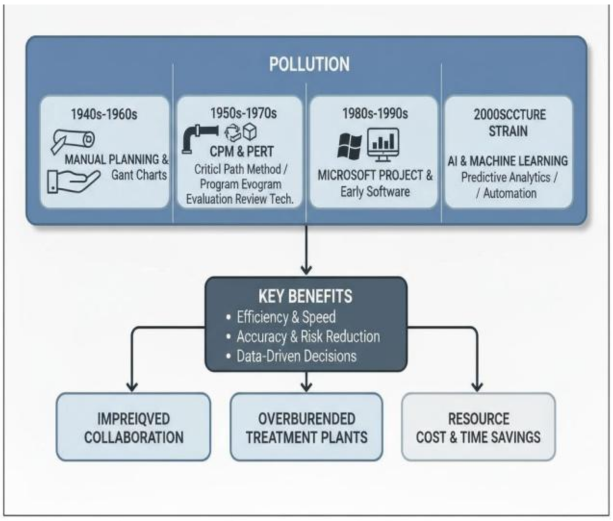

Figure1.1: Evolution of Project Management Methodologies in Construction

Nevertheless, AI implementation in construction management is still young, especially regarding residential construction. The problem of insufficient high-quality datasets, reluctance to embrace technology, and the issue of model interpretability are some of the challenges that impede its extensive use. Moreover, most construction companies still use their traditional practices because they are familiar with them and they are less costly in the short run, although they might not be effective in the long term. Thus, it is fundamental to carefully examine the effectiveness of AI-aided methods against the conventional manual ones to determine their viability in practice [Patel et al., 2023]. The study fills this gap by providing a thorough comparative study of manual and AI-assisted project scheduling and cost estimation tools in construction management. The study aims at measuring the key performance indicators including accuracy in time and cost variation and efficiency in the utilization of resources. The study will offer some valuable insights into the effectiveness, reliability, and scalability of AI-driven solutions by building a Python-based neural network, comparing its results with the traditional ones. The results will be likely to enhance the development of intelligent construction management systems and assist in the digital transformation of the construction industry [Singh et al., 2024].

1.1 Background of the Study

Introduction Construction project management Construction project management is an orderly procedure that entails planning, coordination and regulation of resources to accomplish project objectives under specified constraints including time, cost, quality and scope. It involves different stages such as project initiation, planning, execution, monitoring and closing. Project management is also efficient as to ensure that the construction activities are conducted effectively and are capable of upholding safety standards and regulations. Conventionally, project managers make use of the available methodologies like work breakdown structures (WBS), scheduling, cost estimation practices to direct project implementation. But the growing complexity of contemporary construction projects, particularly in residential projects in cities, has complicated the ability to control numerous variables simultaneously, such as the labour, materials, the environment, and expectations of the stakeholders. Research shows that construction projects are likely to experience delays and cost overrun due to inefficient planning and the absence of real-time decision-making tools [Sharma et al., 2023]. Consequently, there is a pressing need to advance the project management practices in order to increase the productivity and successful project delivery. Significance of Scheduling and Cost Estimation the Project scheduling and cost estimation are the two most important aspects of construction management because they directly determine the success and viability of the project. Scheduling is the process of assigning time to project activities and they are well sequenced and coordinated to eliminate delays. Gantt charts, Critical Path Method (CPM) and Program Evaluation and Review Technique (PERT) are popular methods of creating project schedules. Cost estimation on the other hand deals with estimating the financial needs of a project such as the costs of the materials, labour costs, equipment costs, and overheads. Budgeting, financial planning and allocation of resources require accurate cost estimation. Any mistake in scheduling or cost estimation could have devastating results like delaying the project, cost overrun, and poor quality. Studies indicate that even slight errors during the initial phases of estimation can have a considerable effect on the entire project cycle [Kumar et al., 2024]. Therefore, precision in scheduling and cost estimation is critical towards successful construction project completion and proper management of projects. Limitations of Manual Methods Even though the traditional manual method of project scheduling and cost estimation has been widely used, it faces a number of limitations. Such approaches are heavily dependent on human knowledge, experience, and judgment that can bring about bias and inconsistencies to the decision-making process. Manual computations are usually time consuming and incapable of handling huge amounts of data effectively. Also, traditional methods are usually fixed in place and are not flexible to changes in the project environment, including changes in resource availability or unforeseen delays. This inability to update schedules and cost estimates in real time can be attributed to this lack of flexibility. Moreover, manual methods are generally not successful in capturing the intricate relationships among various parameters in a project, and hence, the result is poor planning and use of resources. Research has revealed that the use of manual procedures escalates the possibility of human error and decreases the overall efficiency of projects [Patel et al., 2023]. These restrictions signify the necessity of sophisticated, information-enabled strategies to enhance precision and versatility in construction management.

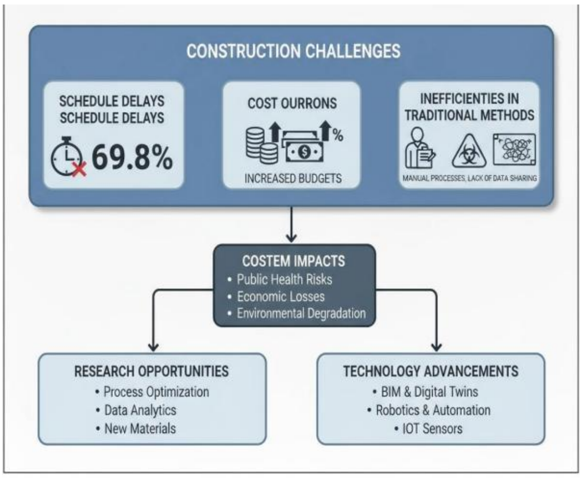

Figure 1.2: Motivation for the Study: Construction Industry Challenges

1.2 Need for AI in Construction Management

The Artificial Intelligence in Construction Artificial intelligence (AI) has become a new powerful technology in the construction sector, as it provides new solutions to overcome the drawbacks of conventional approaches. The analysis of large data sets based on AI methods, including machine learning, neural network, and predictive analytics, can help to discover patterns and provide correct predictions. AI in the management of construction projects can be utilized to optimize project timelines, ensure the accuracy of cost estimation, and optimize resource allocation. To illustrate, machine learning algorithms can be used to evaluate past project data to forecast possible delays and suggest the best scheduling strategies. Likewise, AI-based cost estimation models can deliver a more accurate financial forecast, as they take into account numerous variables at once. All these capabilities radically decrease human intervention and enhance efficiency in decision-making. As research studies have shown, the systems based on AI can be more accurate and reliable than traditional methods, and they can be effectively applied in the context of modern construction management [Guo et al., 2025]. Digital Transformation in Project Management The implementation of digital technologies is leading to a massive shift in the process of managing construction projects, turning away from the traditional methods of managing projects to more intelligent and automated ones. Digital transformation is the adoption of new high-tech solutions including AI, Building Information Modelling (BIM), Internet of Things (IoT), and cloud computing that will contribute to improving efficiency and collaboration of a project. These technologies permit the real-time collection, analysis and visualization of data, which enables the project managers to make informed decisions promptly. With the aid of AI, along with the use of digital platforms, the system may offer more dynamic scheduling, better cost forecasting, and enhanced risk management opportunities. Additionally, the digital tools make communication and coordination among stakeholders easier and less prone to errors and enhancing the overall performance of the project. In spite of these advantages, digital technologies are still being adopted in construction as it is facing the challenge of expensive initial investment and technical skills. Nevertheless, further studies and innovations suggest that digital transformation will become a key factor in the future of the construction project management [Singh et al., 2024].

Figure 1.3: AI-Assisted Construction Management: Comparative Analysis of Manual vs Intelligent Scheduling and Cost Estimation

2.Traditional Project Scheduling Techniques

Among the oldest and most popular project scheduling tools in construction management is the Gantt charts. They give a graphical representation of activities in a project in a timeline which enables project managers to monitor the duration of tasks, start and end dates, and status of a project. Gantt charts are also the most suited in small to medium-sized residential projects because they are simple and easy to read. They cannot however be used to model complex dependencies between tasks and do not well cope with uncertainties or dynamic changes in the conditions of the project. The constraints of the Gantt charts are increasingly clear as construction projects become more and more complicated, especially in large-scale planning and situations of real-time decision-making [Sharma et al., 2023]. One of the most common scheduling tools that are used is the Critical Path Method (CPM), as it helps to identify a series of critical activities that have a direct effect on the time when the project will be ready. CPM is useful in identifying the longest path in a project network by examining dependencies among the tasks and identifying activities whose timing cannot be postponed without impacting the entire project. This is an excellent way of controlling complicated construction works and time management. CPM however, presupposes the uncertainties of the activity time as deterministic, and it might not be consistent with the actual uncertainties in the world, including the weather, labour fluctuations and delay of materials. This means that it might not be accurate in dynamic construction environments [Kumar et al., 2024]. Program Evaluation and Review Technique (PERT) Program Evaluation and Review Technique (PERT) is a sophisticated scheduling technique that takes into account uncertainty through the use of probabilistic time estimates. It takes into account three-time parameters: optimistic, most likely and pessimistic time, which allows the project to be scheduled more flexibly and realistically. PERT is especially applicable in those projects in which the time spent on activities is not known or cannot be estimated precisely. PERT has some complex calculations and needs large amounts of data as its input, which is disadvantageous compared to regular construction projects, though it has its benefits. Also, it can continue to be very subjective, which could influence the quality of findings [Patel et al., 2023].

2.1 Conventional Cost Estimation Methods

In the initial phases of a construction project, Approximate Estimation techniques are applied in order to give a rough

estimate of the project costs. Commonly used quick cost assessment techniques include unit rate estimation, plinth area method and cube rate method. The techniques can be applied in case of feasibility study and preliminary budgeting, but they are not precise and can cause big variations in the final project expenditures. The use of historical data and assumptions also limits their accuracy, particularly when working with a project with special design needs or a variable cost of materials [Singh et al., 2024]. Detailed Estimation is a complete calculation of all the project costs such as cost of materials, labour, equipment and overheads. This technique involves elaborate drawings and specifications, calculation of quantities and analysis of costs. Despite its greater accuracy over approximate methods of estimation, detailed estimation is time consuming and needs a lot of expertise. Cover ups may occur even when there are mistakes in the quantity computations or wrong assumptions. Furthermore, this method does not fit well to address real-time variations in the state of projects [Guo et al., 2025]. Quantity Take-Off Methods are those approaches that are based on the systematic quantification and computation of material quantities needed in construction. These amounts are then utilized to estimate project costs using existing rates in the market. QTO is an essential element of the detailed estimation and is an important part of budgeting and the planning of procurement. Nevertheless, the manual QTO processes are time-consuming and can easily be compromised by human errors especially in the case of complex projects that have huge datasets. The absence of automation also reduces efficiency and accuracy in cost estimation [Lee et al., 2025].

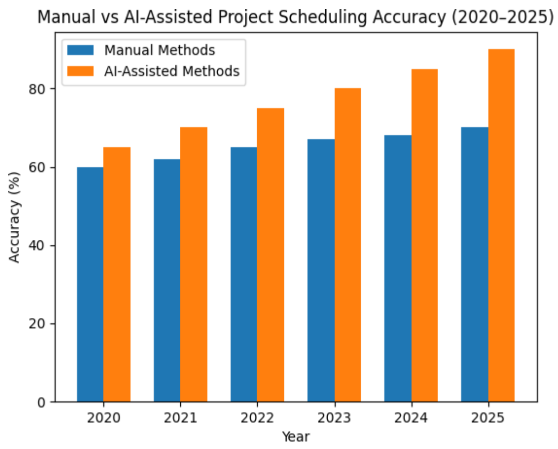

Figure 1.4: Comparative Analysis of Manual vs AI-Assisted Project Scheduling Accuracy (2020–2025)

2.2 AI Techniques in Construction Management

The use of Machine Learning Algorithms in construction management is one area that has received a lot of interest because it can be used to analyse large datasets and establish patterns that can be used to make accurate predictions. Regression analysis, decision trees, and neural networks are all common techniques that are used in predicting costs, durations, and risks of the project. ML models are able to constantly learn new data, enhancing their performance as time goes by. Their capabilities enable them to be very effective in dealing with complex and dynamic construction environments, where conventional procedures might not be able to provide accurate results [Kumar et al., 2024]. Predictive Analytics refers to use of statistical models and data mining method to predict future project outcomes using previous data. Predictive analytics is applied in construction management to estimate the project schedules, possible delays, and predict changes in costs. Data-driven insights will allow project managers to make informed decisions and take proactive actions that will help reduce risks. Research shows that predictive analytics can greatly increase the accuracy and reliability of project planning as opposed to traditional approaches [Singh et al., 2024]. The AI Optimization Techniques are aimed at finding optimal solutions to the problems of scheduling and resource allocation. Genetic algorithms, particle swarm optimization, and linear programming algorithms are popular algorithms to optimize project schedule and reduce the cost. These methods take into account several constraints and goals in one, which allows to optimize the use of resources and increase the performance of the project. AI-based optimization methods offer more accurate and scalable solutions to complex construction projects as compared to manual methods [Guo et al., 2025].

2.3 Review of AI-Based Scheduling Models

Recent research has examined some of the AI based scheduling to enhance construction project management. Artificial neural networks and support vector machines are examples of machine learning models that have been used to estimate project durations and optimization of project scheduling. Also, there have been promising outcomes of hybrid models that use AI techniques and traditional models, like CPM with machine learning, to enhance the accuracy of scheduling. Their ability to be adjusted to real-time data and the changes in the conditions of the project make these models more efficient than traditional scheduling methods. Nevertheless, their application is limited by the availability of data and complexity of models [Patel et al., 2023].

2.4 Review of AI-Based Cost Estimation Models

The models of AI-estimating cost have shown promising potential in enhancing the accuracy and efficiency of the construction cost forecasting. Regression models, neural networks, and deep learning algorithms are common techniques that have been employed to make predictions on the costs of a project, using historical data and project parameters. Large datasets and complex relationships between variables can be dealt with in these models, leading to more accurate cost estimates. The studies show that AI-based models are more accurate and reliable compared to the traditional estimation techniques. The success of these models however relies on the quality and availability of data, which is a major challenge in real-life applications [Lee et al., 2025].

2.5 Comparative Studies: Manual vs AI-Based Methods

A number of studies have made comparative studies on the use of manual and AI-based strategies in construction management. The results always show that AI-assisted solutions are more accurate, efficient, and cost-effective in terms of resource optimization, than conventional solutions. Manual methods are easy and well-known but cannot process large volumes of data and cope with alterations of project conditions. Conversely, AI-driven systems can provide information-driven insights, real-time updates, and predictability, which will improve decision-making and project performance. In spite of these benefits, AI has not yet been widely adopted in construction as it has been facing challenges like high cost of implementation and insufficient technical skills. Consequently, additional studies are still needed to overcome the gap between old and new methods and facilitate the adoption of AI in construction management activities [Singh et al., 2024].

Figure 1.5: Publication Distribution in AI-Based Construction Scheduling and Cost Estimation

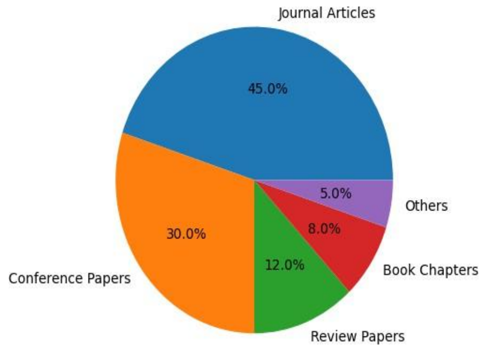

Table 1. Comparative Analysis of AI-Based Multi-Sensor Fusion Techniques for Non-Invasive Liquid Recognition

Ref.	Year	Data Modality	Objective / Scope	Technique / Architecture	Explainability	Federated Learning	Key Findings	Research Gaps and Open Challenges
[1]	2023	Historical project data, schedules	Analyse manual scheduling efficiency	CPM, Gantt Charts	High	No	Manual methods are simple but time-consuming and less accurate	Lack of adaptability to dynamic conditions
[2]	2023	Cost datasets, BOQ	Evaluate traditional cost estimation	Quantity Take-Off, Detailed Estimation	High	No	Reliable but prone to human error and delays	Limited automation and scalability

[3]	2024	Structured project datasets	Improve scheduling accuracy	Machine Learning (Regression Models)	Medium	No	ML improves prediction accuracy significantly	Requires large datasets and preprocessing
[4]	2024	Time-series construction data	Predict project delays	Predictive Analytics	Medium	No	Early delay prediction enhances planning efficiency	Model generalization issues
[5]	2025	Multi-project datasets	Optimize cost estimation	Neural Networks (ANN)	Low	No	AI models outperform traditional estimation methods	Lack of interpretability
[6].	2025	BIM + project data	Integrate AI in construction workflows	Deep Learning + BIM Integration	Low	No	Improved automation and decision-making	High implementation complexity
[7]	2024	Resource & scheduling data	Optimize resource allocation	Genetic Algorithm (GA)	Medium	No	Efficient resource utilization achieved	Computational cost is high
[8]	2023	Real-time sensor & project data	Dynamic scheduling	IoT + AI-based models	Medium	Yes	Real-time updates improve scheduling accuracy	Data security and integration challenges
[9]	2025	Large-scale construction datasets	Cost prediction at scale	Deep Learning (LSTM)	Low	Yes	High accuracy in cost forecasting	Requires high computational power
[10]	2024	Mixed structured/unstructured data	Comparative study manual vs AI	Hybrid Models (CPM + ML)	Medium	No	AI-assisted methods reduce cost deviation and delays	Lack of standard frameworks

3.Synthesis of Previous Research

The past researches on construction project management emphasize that the traditional manual tools like the Gantt charts, CPM and PERT have been commonly utilized in scheduling and cost estimation in projects because of their simplicity and simplicity in implementation. Nevertheless, these methods are usually constrained by lack of ability to deal with uncertainties, dynamic project conditions, and high volume of data, leading to inefficiencies, delays, and excess costs [3-11], Studies have shown that the manual estimation methods are heavily dependent on expert judgment and therefore, they tend to be subject to human errors and discrepancies, especially where complex residential and infrastructure projects are involved [7-36].

Along with the development of digital technologies, artificial intelligence (AI) and machine learning (ML) have become a potent tool to enhance construction project management practices. AI-based models have exhibited considerable enhancement in the accuracy of the scheduling, delay prediction, and cost estimation by utilizing the past data and real-time information [2-8], For example, machine learning models like regression models, neural networks, and gradient boosting techniques have proved to have a high predictive accuracy in estimating the project timelines and costs and have made a tremendous improvement in predicting costs and delays when compared to the traditional models. Moreover, predictive analytics has been heavily implemented to detect possible risks and optimize resource usage, which has resulted in improved decision-making and improved project results [5-14],

There is also recent literature about the combination of AI with the latest technologies like Building Information Modelling (BIM), Internet of Things (IoT), and digital twins, which allow real-time monitoring and dynamic project control. These combined systems enable ongoing revision of schedules and cost estimates due to the real-life situations in the sites hence enhance flexibility and efficiency [29-47]. Research has demonstrated that AI-based systems could save up to 30-percent of the planning time and optimize schedules, which indicates their effectiveness in overcoming the drawbacks of manual systems, and AI-based frameworks that implement deep learning and reinforcement learning have been effectively used to optimize resource use and enhance the predictability of costs in large-scale projects.

Although such improvements exist, there are still a number of issues with the implementation of AI in the field of construction management. The quality and availability of data are vital challenges, because AI models need massive and quality data to train and validate. Also, the inability to interpret complicated models, including deep learning algorithms, poses challenges to earning trust among professionals in the industry [9-55]. The cost of implementation is high, and integration with existing systems is complicated, and technological resistance further impedes the adoption of AI-based solutions [12-59]. Furthermore, explainable AI (XAI) studies in the construction sector are not extensive, and the focus should be on developing a transparent and interpretable model that can be used to facilitate a decision-making process in general. The AI technologies can revolutionize the construction project management through data-driven planning and real-time monitoring, as well as predictive decision-making. However, more studies are needed to overcome the current challenges and come up with standardized, reliable and cost-efficient AI systems to be implemented in construction industry [4- 48].

3.1 Performance Evaluation Metrics

The performance evaluation metrics are important to measure and compare the efficiency of manual and AI-assisted in construction project scheduling and cost estimation. These measures allow a quantitative analysis of the accuracy, efficiency, and optimisation of the results through advanced computational methods. Compliance with the set schedules, cost control and efficient use of the resources available are some of the factors that define project success in construction management. Thus, the proposed research will use three major performance indicators (KPIs) such as time accuracy, cost deviation, and resource utilization efficiency to compare the performance of the traditional and AI-based approaches. These measurements are common in the literature as crucial indicators to assess the project performance and the efficiency of decision-making in dynamic construction settings [Kumar et al., 2024], [Singh et al., 2024].

3.2 Time Accuracy

Time accuracy is the degree to which the planned project schedule matches the actual time that it will take to complete the construction activities. It is a key performance indicator because construction project delays can lead to cost escalation, contract fines and client dissatisfaction. Most manual scheduling tools (CPM and Gantt charts) are usually based on deterministic assumptions and human judgment, which commonly does not consider uncertainties, like weather fluctuations, labour productivity variations, and supply chain upsets. Therefore, these techniques can create timetables that could be quite different to the real project schedules [Sharma et al., 2023]. Conversely, AI-based scheduling systems apply machine learning algorithms and predictive analytics to process past project data and determine patterns that affect project times. Such models are able to dynamically change schedules depending on real-time inputs, and this enhances the accuracy of forecasting. The accuracy of time is often determined by the percentage deviation or error, the time planned versus the time actually completed. According to research studies, AI-based scheduling approaches can greatly minimize time estimation errors and enhance on-time project delivery in comparison to the traditional approaches [Guo et al., 2025]. Increased time accuracy does not only guarantee timely completion but also enhances coordination with the stakeholders and efficiency in the project.

3.3 Cost Deviation

Cost variation can be explained as the difference between the estimated project cost and the actual cost incurred in the project implementation, expressed in percentage. It is a serious measure of the accuracy and efficiency of the cost estimation techniques. Other traditional methods of manual estimation, including approximate estimation and detailed quantity take-off, are highly subjective, based on assumptions, past experience, and manual calculations. The methods fail to cope

with the changes in the prices of materials, labour expenses, and unexpected situations in projects, which often result in critical cost increases [Patel et al., 2023]. To overcome these weaknesses, AI-based cost estimation models can take into account many different variables and use big data to produce more precise estimates. Regression analysis, artificial neural networks, and deep learning models are some of the techniques that are able to capture the complex relationship between project parameters leading to better cost forecasting. Cost deviation is determined through a comparison between the actual expenditure and the estimated cost with the lower deviation implying greater precision in the estimation. Research has revealed that AI-based cost estimation techniques may minimize the cost variance dramatically, thus improving financial management and project viability [Lee et al., 2025]. Effective budgeting, allocation of resources, and reduction of financial risks in construction projects can only be achieved with accurate cost estimation.

3.4 Resource Utilization Efficiency

Resource utilization efficiency is the level at which project resources, such as labour, materials and equipment, are deployed and used efficiently during the project life-cycle. Effective resource management is essential in maximizing productivity, minimization of waste and cost reduction of projects. In conventional manual methods, allocation of resources is in most cases determined by fixed schedules and inadequate information which may lead to either underutilization, over-allocation or idle time. Such inefficiencies affect the performance of the project adversely and raise the total costs [Singh et al., 2024]. The use of AI-assisted procedures optimizes the use of resources through the use of optimization algorithms and data-driven decision-making strategies. State-of-the-art techniques like genetic algorithms, particle swarm optimization, and machine learning-based resource planning models allow the identification of the best allocation strategies under different constraints. These systems are able to load balance the resources allocation according to the real time project conditions, which enhances efficiency and minimizes wastage. The efficiency of resource utilization is usually measured by comparing the planned resource utilization and actual utilization and determining deviations. Studies have shown that optimization methods implemented by AI enhance resource efficiency, resulting in enhanced productivity and lower costs of operations [Guo et al., 2025], [Kumar et al., 2024].

Table 2: Comparative Analysis of Manual and AI-Based Techniques for Project Scheduling and Cost Estimation

Study Type	Data Modality	Model Used	Accuracy (%)	Sensitivity (%)	Limitations
Traditional Manual Approach	Historical project data, schedules	Gantt Chart, CPM	60–70	55–65	Time-consuming, prone to human error, lacks adaptability
Conventional Cost Estimation	BOQ, material & labour data	Approximate & Detailed Estimation	65–72	60–68	Depends on assumptions, low precision in dynamic conditions
Machine Learning-Based Study	Structured project datasets	Linear Regression, Decision Trees	75–85	70–80	Requires large datasets, preprocessing complexity
Predictive Analytics Approach	Time-series project data	Statistical & Forecasting Models	78–88	72–85	Limited generalization, sensitive to data quality
Neural Network-Based Study	Multi-dimensional construction data	Artificial Neural Networks (ANN)	82–92	80–90	Lack of explainability, high computational cost
Deep Learning-Based Approach	Large-scale project datasets	CNN, LSTM	85–95	83–93	Requires high computational power and training time
Hybrid AI Model	Mixed structured/unstructured data	ML + Optimization (GA, PSO)	88–96	85–94	Complex implementation, integration challenges
AI + BIM Integration Study	BIM + real-time project data	Deep Learning + BIM	90–97	88–95	High cost, requires technical expertise
IoT + AI-Based Study	Sensor data + project data	IoT + ML Models	87–94	84–92	Data security and integration issues

4.Research Gap Identification

The analysis of the current literature on construction project scheduling and cost estimation indicates that there is a considerable progress in the conventional and AI-based approaches. Traditional manual methods, such as Gantt charts, Critical Path Method (CPM), and in-depth cost estimation methods have gained wide acceptance because they are simple and easy to implement. But all these approaches are necessarily constrained by the need to rely on the expertise of humans, on the assumptions that are not constantly updated, and the inability to fit the dynamic project environment. Consequently, they tend to cause poor scheduling, cost escalation, and poor use of resources especially in complicated residential construction projects [Sharma et al., 2023], [Patel et al., 2023]. Despite enhanced performance and accuracy of AI-based methods like machine learning, predictive analytics, and optimization algorithms, there are still a number of research gaps. To begin with, the majority of the studies that are currently carried out look at scheduling or cost estimation in isolation, with little incorporation of the two factors into a single framework. This prevents the possibility of holistic modelling to attain a complete project optimization [Kumar et al., 2024]. Secondly, most AI models are trained on controlled or simulated data, which restricts their relevance to real-world construction worlds where data tends to be incomplete, noisy, and inconsistent [Singh et al., 2024].

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The absence of user-friendly tools and practical implementation is another critical gap. Although state-of-the-art AI models are promising in research, they have not entered the construction industry yet because the software solutions that can be readily utilized by engineers and project managers are not available. Moreover, the application of AI models in the structural design process, especially in residential buildings, e.g., G +2 buildings, has not been adequately pursued [Guo et al., 2025]. This underscores the importance of having an integrated system that integrates design, scheduling and cost estimation in one platform.

Besides, the current AI-based solutions are frequently not explainable and transparent, which does not provide practitioners with an opportunity to trust and interpret the findings. The black-box character of sophisticated models like deep learning makes it difficult to make decisions and restricts their adoption in the industry. In addition, data security, standardization, and interoperability with the existing construction management systems are other problems that make AI technologies less widespread [Lee et al., 2025].

Last but not least, there are no extensive comparative studies that quantitatively measure the performance of manual and AI-assisted approaches in terms of such standardized measures as time accuracy, cost deviation and resource utilization efficiency. The majority of research revolves around case studies without a comparative analysis of several performance measurements. Thus, this gap is in need of research that would fill it by establishing an integrated AI-assisted framework and provide a thorough comparative analysis of it with conventional methods. This paper seeks to fill these gaps by creating a Python-based AI-assisted application that combines project scheduling, cost estimation and structural design, and then performs a thorough performance comparison with the manual methods. The results will be used to enhance intelligent, efficient and practical construction management solutions.

5.Results And Discussion

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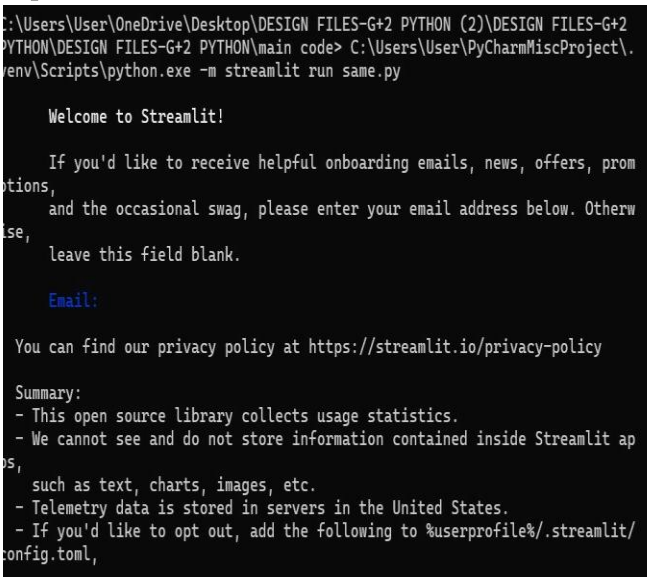
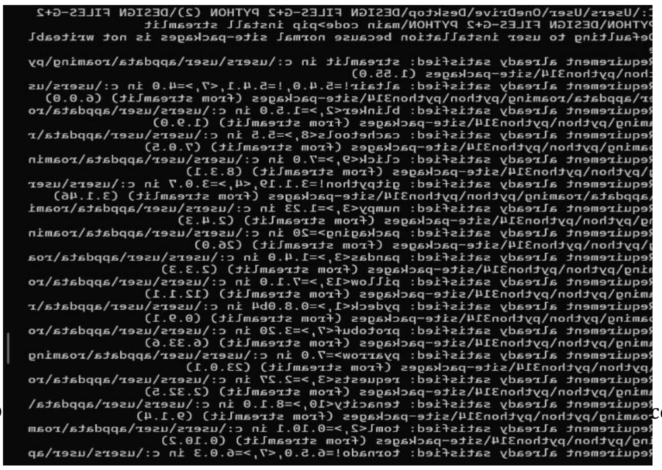
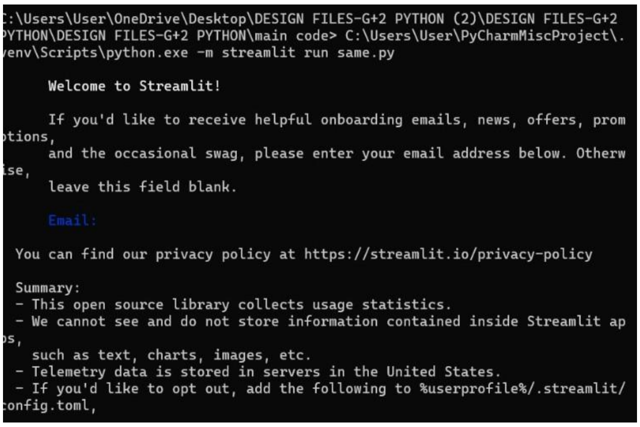
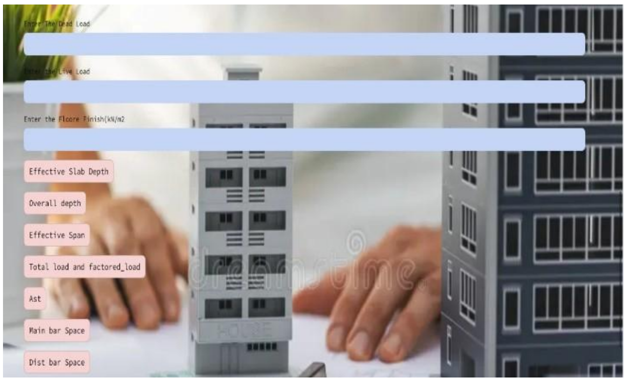






DESIGNING A G2 STRUCTURE USING PYTHON WITH GUT



CAD Design Plan

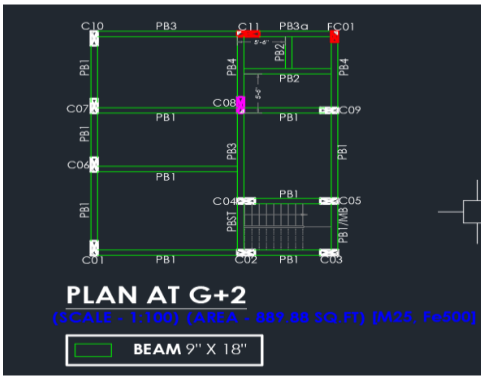


Figure1.6: CAD Design Plan

Structural plans indicate the location of beam and column to enable construction that is safe and efficient and show accuracy in terms of labelling. They also give the required dimension and layout of the material to estimate properly and allocate resources.

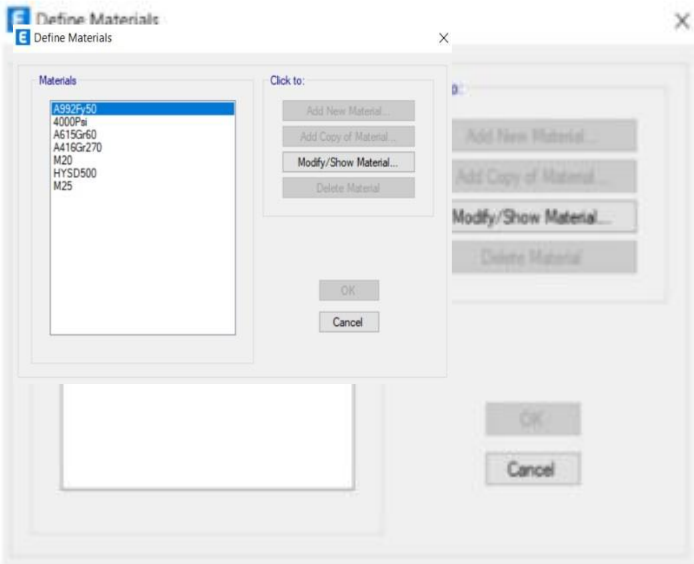


Figure1.7: Material Defined

The dialog window contains a material list that is commonly available in structural design software to specify construction properties. The typical materials are high-strength steel (A992Fy50, HYSD500), concrete grade (M20, M25), and rebar grade (A615Gr60, A416Gr270).

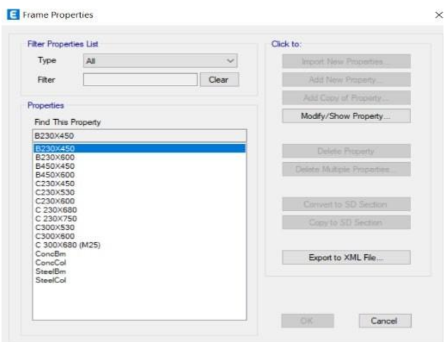


Figure1.8: Frame Properties

It gives frame properties (beam and column cross-section) to structural modelling software, with standard steel (e.g. B230X450, Steel Col) and concrete sections (e.g. C300X600, Cone Col).

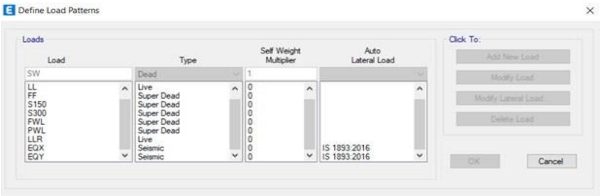
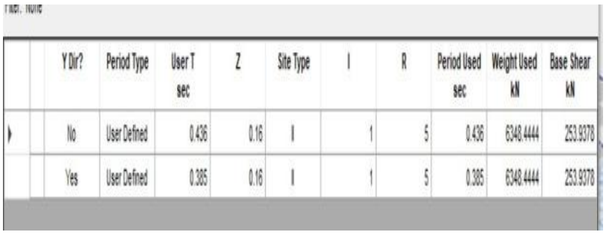


Figure1.9: Define Load Patterns

Dialog divides various structural load types such as Dead, Live, Super Dead, and Seismic into analysis. The calculation of lateral load is automated in standard codes (IS 1893:2016) in relation to earthquake safety.



Y Dir?	Period Type	User T sec	Z	Site Type	I	R	Period Used sec	Weight Used kN	Base Shear kN
No	User Defined	0.436	0.16	I	1	5	0.436	6348.4444	253.9378
Yes	User Defined	0.385	0.16	I	1	5	0.385	6348.4444	253.9378

Figure1.10: Maximum Base Shear

Table presents the seismic analysis results of both X and Y direction with periods, zone factor (Z = 0.16) and base shear values provided by the user. Both directions have the same building weight (6348.4444 KN) and base shear force (253.9378 KN) with emphasis on the earthquake-resistance design parameters.

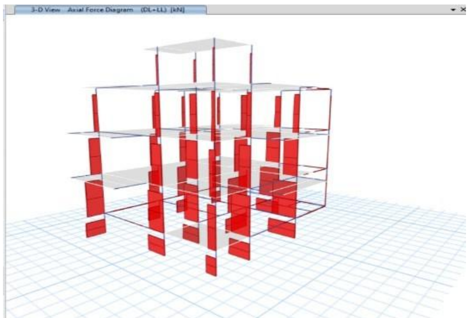


Figure 1.11: Axial Force Diagram

The picture shows a 3D axial force diagram of a multi-story building model, in which the columns are where there is a lot of axial loading. This visualization plays a crucial role in understanding load distribution, and designing columns in a manner that is stable and safe.

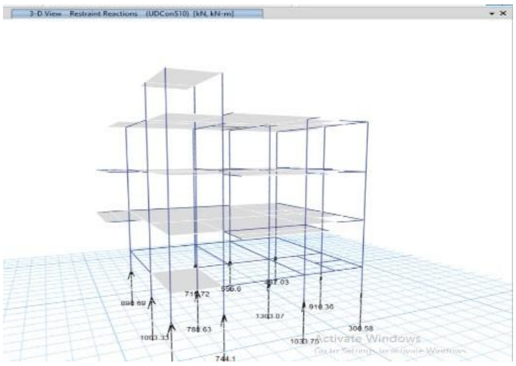


Figure1.12: Restraint Reactions

The picture demonstrates the support reactions within a building frame, the allocation of the forces at the column bases which are important in making the engineers justify foundation design and provide stability by analysing the loads that are spread to the supports.

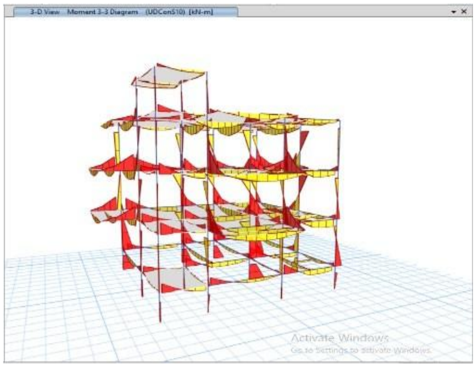


Figure1.13: Moment 3-3 Diagram

The picture depicts a 3D moment diagram of a building frame, with the coloured lines representing the intensity of bending moment in structural members. This helps the engineers to determine the required reinforcement and enhance the

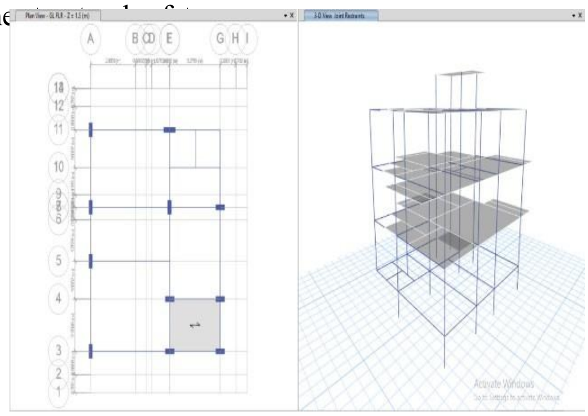


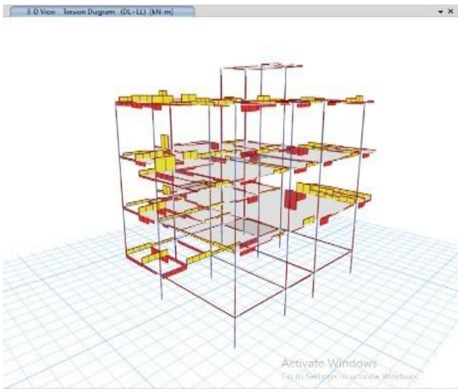
Figure1.14: Plan and Elevation

The report presents a structural model with a 2D plan view, which highlights support or restraint points of joints on the left and a 3D wireframe view to the right.

Figure1.15: Shear Force 2-2 Diagram

The picture shows a 3D shear force diagram which indicates the magnitude and location of shear forces on beams and columns of a multi-story structure. High shear demand is shown by red and yellow regions, and it helps structural engineers to strengthen members to ensure safety.

Figure 1.16: Torsion Diagram



The picture features a 3D torsion diagram of a structure, highlighting torsional moments on beams and floor slabs with red and yellow lines. These plots aid engineers in pointing out the critical areas where twisting can occur and this is used to decide what reinforcement should be made or the design to be changed.

Analysis Results
Maximum Storey Displacement

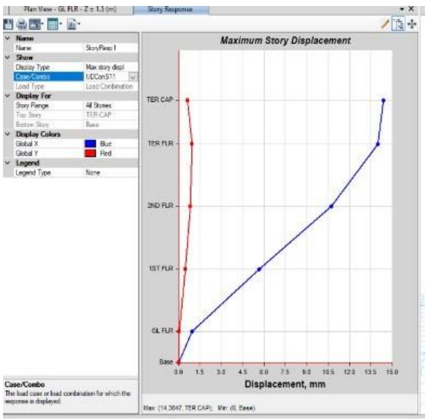


Figure1.17: Maximum Storey Displacement

The graph shows the maximum story displacement at any building with blue lines and red lines showing the lateral displacement in the X and Y directions respectively at every level in the building. The values of displacement increase with height, which helps the engineers to assess the structural flexibility and serviceability with load combinations.

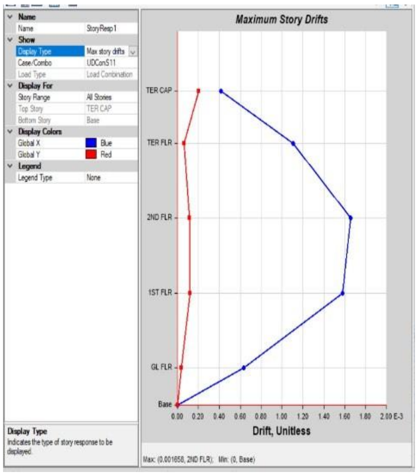


Figure 1.18: Maximum Storey Drifts

The chart shows the largest story drifts by the floor, with the blue and red lines showing X and Y drifts respectively. The latter values are vital in determining the lateral deformation between floors, especially in determining earthquake performance and structural safety.

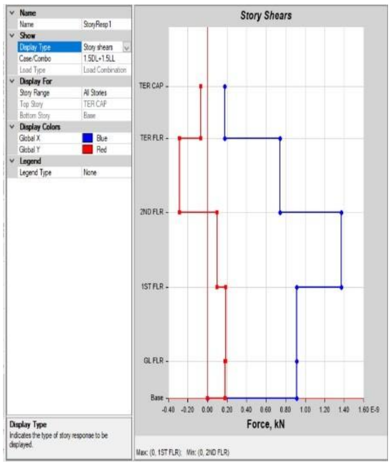


Figure1.19: Story Shears

The forces of story shear (in KN) are shown in the plot at each floor level, and the colours blue and red show the forces in the global X and Y directions. Story shears are important in determining how much lateral force needs to be resisted by each story which is essential in determining the earthquake and wind performance of the building.

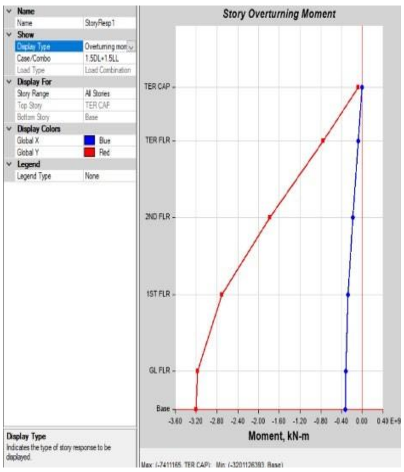


Figure1.20: Story Overturning Moment

The graph indicates story overturning moments (in kN-m) on each floor, where the blue and red lines indicate overturning on the X and Y global directions, respectively. The moment plots (overturning) are used to assess the stability of the building under lateral forces to ensure that the building has the ability to resist falling over in case of occurrence of events such as earthquakes and strong winds.

6.Conclusion

This chapter has been an extensive survey of conventional and AI-aided methods of scheduling and cost estimation of projects in construction management. They talked about conventional approaches, including Gantt charts, CPM, PERT, and manual cost estimation techniques, with their simplicity and popularity in residential construction projects. These approaches however have their shortcomings in the fact that they require human input, are not flexible to dynamic environments and are prone to errors that tend to create delays and cost overruns.

The review also discussed how artificial intelligence methods such as machine learning, predictive analytics, and optimization algorithms have been used to enhance the practices of construction project management. The Ai-based solutions also have enormous prospects in increasing the quality of scheduling, minimizing cost fluctuations, and maximizing resource use due to data-driven decision-making and real-time analysis. Moreover, the introduction of new technologies like BIM and IoT have also boosted the power of AI systems in building sites.

Regardless of these developments, a number of issues are still evident, such as the availability of data, the complexity of the models, their uninterpretability, and their inability to be applied to real-life projects. The review also found that there is a deficiency in the overall frameworks that can contribute scheduling, cost estimation, and structural design into a single system, lack of comparative studies by utilizing standardized performance metrics.

On the whole, the results suggest that although traditional approaches remain applicable to simple tasks, AI-assisted ones are more effective regarding accuracy, efficiency, and scalability. The shift to intelligent construction management systems is needed to manage the increasing complexity of modern projects and enhance the results of the whole project.

The present study preconditions the creation of a combined AI-based system and the in-depth comparative analysis of the new technologies in support of their implementation in the construction industry.

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