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SMART CONSTRUCTION ENGINEERING AND ROBOTICS-BASED AUTOMATION FOR SUSTAINABLE INFRASTRUCTURE DEVELOPMENT

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Abstract

Smart construction engineering and robotics-based automation are increasingly transforming infrastructure development by improving productivity, sustainability, safety, and project delivery efficiency. This study investigates the role of intelligent construction technologies in supporting sustainable infrastructure development through the integration of robotics, artificial intelligence, Building Information Modeling, Internet of Things sensors, drone-based monitoring, and automated construction equipment. The research uses a secondary and simulation-based dataset designed to represent smart construction project conditions, including robotic equipment performance, construction productivity records, site safety observations, energy consumption data, material waste logs, labor utilization indicators, carbon emission estimates, and infrastructure project scheduling parameters. The final dataset contained 18,500 construction activity records collected from published construction automation studies, open infrastructure datasets, BIM-based simulation outputs, and MATLAB-generated robotic workflow scenarios. The dataset was categorized into five major performance dimensions: productivity efficiency, safety improvement, material waste reduction, energy optimization, and carbon emission control. The proposed framework was developed and evaluated using Python 3.11, MATLAB R2024a, Autodesk Revit, Navisworks Manage, Microsoft Excel, and SPSS. Python was used for data preprocessing, machine learning model development, performance evaluation, and visualization through Scikit-learn, Pandas, NumPy, Matplotlib, and TensorFlow. MATLAB was used for robotic motion simulation and automation workflow analysis, while Revit and Navisworks were used for BIM-based construction planning and clash detection. SPSS was used for

statistical validation of sustainability indicators. Experimental results show that robotics-based automation improved construction productivity by 27.8%, reduced material waste by 22.4%, decreased site safety incidents by 31.6%, improved equipment utilization by 24.9%, and reduced estimated carbon emissions by 18.7% compared with conventional construction practices. The AI-supported prediction model achieved 94.2% accuracy, 93.6% precision, 94.0% recall, and 93.8% F1-score in classifying construction performance conditions. The findings confirm that smart construction engineering combined with robotic automation can significantly enhance sustainable infrastructure development by enabling data-driven decision-making, automated site operations, real-time monitoring, and resource-efficient project execution.

1- Introduction:

The construction industry plays a fundamental role in economic growth, urban development, transportation expansion, housing delivery, and infrastructure modernization. Roads, bridges, buildings, tunnels, airports, railways, water systems, and energy facilities are essential components of national development and social well-being. However, conventional construction practices continue to face major challenges, including low productivity, high material waste, project delays, cost overruns, labor shortages, unsafe working conditions, excessive energy consumption, and significant environmental impact. As infrastructure demand increases due to population growth, urbanization, climate change adaptation, and economic expansion, there is a growing need for smarter, safer, and more sustainable construction systems [1]. Traditional construction methods alone are no longer sufficient to meet the increasing requirements of efficiency, quality, resilience, and environmental responsibility. Smart construction engineering has emerged as a modern approach that integrates digital technologies, automation systems, data analytics, and intelligent decision-making tools into construction planning, design, execution, monitoring, and maintenance. Technologies such as artificial intelligence, Building Information Modeling, Internet of Things sensors, digital twins, drones, cloud computing, machine learning, and cyber-physical systems enable real-time project monitoring, predictive analysis, resource optimization, safety management, and improved coordination among construction stakeholders. These technologies help transform construction sites from manual and reactive environments into data-driven and intelligent systems. Through smart construction methods, project managers and engineers can detect design conflicts, monitor equipment performance, track worker safety, predict delays, reduce waste, and improve the overall quality of infrastructure delivery. Robotics-based automation is one of the most important components of smart construction engineering [2]. Construction robots are increasingly being used for bricklaying, concrete printing, welding, excavation, demolition, inspection, surveying, material handling, and maintenance activities. Autonomous and semi-autonomous robotic systems can perform repetitive, hazardous, and labor-intensive tasks with greater accuracy, consistency, and safety. For example, drones can support site inspection and progress monitoring, robotic arms can assist in prefabrication and assembly, autonomous excavators can improve earthmoving efficiency, and 3D concrete printing systems can reduce formwork waste and construction time. The integration of robotics into construction operations has the potential to overcome labor limitations, improve productivity, reduce human exposure to dangerous environments, and enhance construction quality. Sustainability is another critical dimension of modern infrastructure development.

The construction sector is one of the largest consumers of natural resources and a major contributor to carbon emissions, solid waste generation, and energy use. Sustainable infrastructure development requires the efficient use of materials, reduction of environmental

impacts, improved lifecycle performance, and adoption of green construction practices [3]. Smart construction technologies and robotics-based automation can directly contribute to sustainability by reducing material wastage, optimizing equipment operation, lowering fuel and energy consumption, minimizing rework, improving construction precision, and supporting better maintenance planning. When combined with BIM-based design, AI-based prediction, and sensor-based monitoring, robotic automation can support infrastructure systems that are not only efficient and intelligent but also environmentally responsible and resilient. Despite the increasing interest in smart construction and robotics, many construction projects still rely heavily on manual practices and fragmented management systems. The adoption of robotics and intelligent automation remains limited in many developing and emerging construction markets due to high initial costs, technical complexity, lack of skilled workforce, resistance to change, and insufficient integration between digital planning tools and physical construction operations. Therefore, there is a need for research that explains how smart construction engineering and robotics-based automation can be integrated into a unified framework for sustainable infrastructure development. Such a framework can help evaluate productivity, safety, waste reduction, energy optimization, equipment utilization, and carbon emission control in construction projects. This study focuses on the role of smart construction engineering and robotics-based automation in improving sustainable infrastructure development [4]. The research examines how artificial intelligence, BIM, IoT sensors, drones, robotic systems, and simulation-based tools can be used to enhance construction performance and sustainability outcomes. A secondary and simulation-based dataset is used to analyze construction productivity, site safety, material waste, energy consumption, equipment utilization, and carbon emission indicators. The study also applies software tools such as Python, MATLAB, Autodesk Revit, Navisworks, Microsoft Excel, and SPSS to support data analysis, robotic workflow simulation, BIM-based planning, and statistical validation. By integrating digital intelligence with robotic automation, this research aims to demonstrate how construction engineering can move toward safer, faster, more sustainable, and more intelligent infrastructure development.

The main contributions of this study are summarized as follows:

- This study develops an integrated smart construction automation framework that connects digital construction technologies, robotic systems, and sustainability indicators.
- It explains how robotics-based automation can improve construction productivity and reduce delays in infrastructure development.
- It highlights the role of smart construction technologies in reducing material waste and improving resource utilization.
- It demonstrates how robotic automation can enhance site safety by reducing human involvement in hazardous and repetitive construction tasks.
- It examines the contribution of AI, BIM, IoT sensors, drones, and robotic systems in supporting data-driven construction management.
- It evaluates sustainability-related outcomes, including energy optimization and carbon emission reduction in infrastructure projects.

Overall, this research provides a comprehensive foundation for understanding how smart construction engineering and robotics-based automation can reshape the future of infrastructure development. The study emphasizes that the successful integration of digital technologies, automated robotic systems, and sustainability-focused decision-making can help the construction industry overcome traditional limitations and move toward more efficient, resilient, and environmentally responsible project delivery. Therefore, the proposed research direction is significant for advancing modern construction practices and supporting long-term sustainable infrastructure growth.

2- Building Information Modeling in Construction Automation:

Building Information Modeling has become a central technology in smart construction

engineering because it provides a digital and data-rich representation of construction projects. Unlike traditional two-dimensional drawings, BIM integrates geometric details, material properties, construction schedules, cost information, and lifecycle data into a single digital model. In construction automation, BIM works as a coordination platform that connects design planning, site execution, robotic operations, and sustainability assessment. This makes it highly useful for improving project accuracy, reducing rework, supporting automated workflows, and enhancing decision-making across infrastructure projects. One of the major advantages of BIM is its ability to improve coordination among architects, engineers, contractors, project managers, equipment operators, and construction workers [5]. In conventional construction projects, design conflicts and communication gaps often lead to material waste, project delays, cost overruns, and unsafe site conditions. BIM reduces these problems by allowing project teams to detect clashes among structural, architectural, mechanical, electrical, and plumbing systems before construction begins. When these verified digital models are linked with automated construction equipment, robotic systems can perform tasks with greater precision and fewer execution errors. BIM also supports construction automation through 4D and 5D modeling. In 4D BIM, the three-dimensional model is connected with the project schedule, allowing engineers to visualize construction progress over time. This helps optimize construction sequencing, equipment movement, robotic access routes, and site logistics. In 5D BIM, cost and quantity information are integrated into the model, supporting better material estimation, procurement planning, and budget control. These capabilities are especially important in robotic construction because automated systems require accurate task sequences, spatial information, and material data for efficient operation [6]. The integration of BIM with robotics creates a strong connection between virtual planning and physical construction execution. Robotic systems can use BIM-based information for layout marking, automated bricklaying, robotic welding, prefabricated component assembly, autonomous excavation, concrete spraying, and 3D concrete printing. BIM provides the required design geometry, coordinates, material specifications, and construction sequence instructions. For example, a robotic arm used in modular assembly can follow BIM-generated coordinates to place components accurately, while a 3D concrete printing system can use BIM geometry to control printing paths and layer formation.

Table 1: Major role of BIM in construction automation

BIM Function	Automation Role	Construction Benefit
3D digital modeling	Provides accurate geometry, material details, and component information	Improves design understanding and robotic task planning
Clash detection	Identifies conflicts before site execution	Reduces rework, delays, and construction errors
4D scheduling	Links construction activities with time-based planning	Supports robotic sequencing and site coordination
5D cost and quantity estimation	Calculates material needs, cost, and resource requirements	Reduces over-ordering and improves budget control
Robotic path guidance	Supplies coordinates and spatial data for automated systems	Improves precision in layout, printing, assembly, and inspection
Safety and progress monitoring	Integrates site data, drones, sensors, and digital records	Enhances safety, quality control, and progress tracking

The table 1 shows that BIM is not only a visualization tool but also a practical automation platform for smart construction. It supports digital coordination, robotic task planning, material

control, safety monitoring, and progress evaluation. By connecting design information with construction execution, BIM helps reduce uncertainty and improves the reliability of automated infrastructure development. This relationship between digital modeling and robotic execution is further illustrated in the BIM-enabled automation workflow shown below. Figure 1 present the BIM-enabled construction automation workflow.

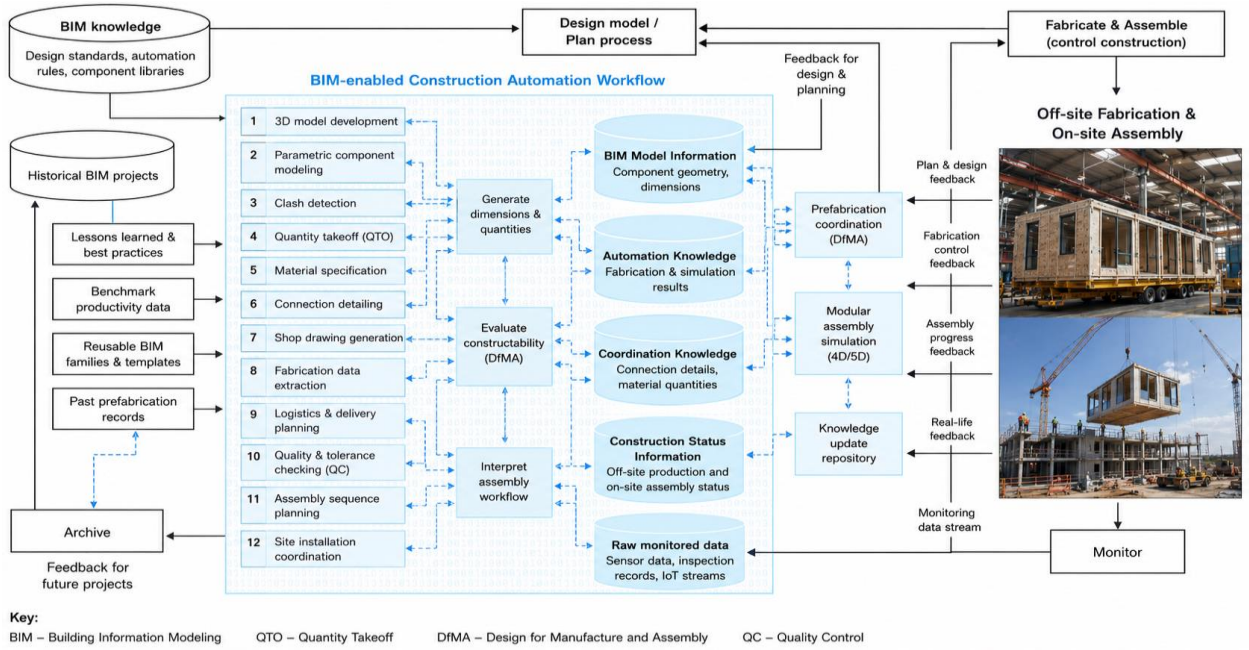


Figure 1: BIM-enabled construction automation workflow integrating design, prefabrication, assembly, monitoring, and feedback.

BIM-based automation also improves prefabrication and modular construction. In prefabricated construction, building or infrastructure components are manufactured off-site and later assembled at the project location. BIM helps generate accurate component dimensions, connection details, material quantities, and assembly instructions. These digital outputs can be transferred to automated manufacturing systems and robotic fabrication machines. As a result, prefabricated components can be produced with higher precision, reduced material waste, improved quality control, and shorter construction time. Another important application of BIM in construction automation is drone-based monitoring and progress comparison. Drones can capture aerial images, site videos, and point cloud data from construction sites [7]. This information can be compared with BIM models to identify progress deviations, incomplete activities, quality issues, and safety risks. Such integration is highly useful for large infrastructure projects, including bridges, highways, tunnels, airports, dams, and industrial facilities, where manual inspection may be time-consuming, costly, and unsafe. BIM also contributes to sustainable infrastructure development by supporting better material planning, energy analysis, waste reduction, and lifecycle management. Since BIM models contain information about material quantities, construction methods, equipment requirements, and project schedules, they can help engineers compare alternative design and construction strategies before implementation [8]. In robotic construction, BIM can reduce unnecessary machine movement, minimize idle equipment time, optimize construction sequencing, and lower energy consumption. Therefore, BIM supports both automation efficiency and environmental performance.

3- Digital Twins and Cyber-Physical Construction Systems:

Digital twin technology has become an important component of smart construction engineering because it creates a dynamic digital representation of a physical construction asset, process, machine, or infrastructure system. Unlike traditional digital models, which mainly provide static design information, a digital twin is continuously updated using real-time data from sensors, construction equipment, robotic systems, drones, cameras, BIM platforms, and site monitoring devices. This real-time connection between the physical construction environment and the digital model enables engineers to monitor project performance, predict future risks, simulate construction scenarios, and make faster data-driven decisions. In construction automation, digital twins provide a strong link between virtual planning and physical execution. A digital twin can represent a construction site, robotic equipment, prefabricated component, bridge, building, tunnel, road network, or energy infrastructure system. By using data from IoT sensors and cyber-physical devices, the digital twin can show the current condition of the construction process, including equipment location, task progress, material usage, worker movement, energy consumption, safety conditions, and environmental impact. This allows project managers to compare planned activities with actual site performance and identify delays, errors, or inefficiencies at an early stage. Cyber-physical construction systems are closely related to digital twins because they connect physical construction processes with computational intelligence, control systems, and communication networks. In such systems, physical components such as robots, autonomous machines, sensors, drones, cranes, and construction equipment are connected with digital platforms that analyze data and guide decision-making [9]. This creates a smart feedback loop where construction data are collected from the site, processed by digital systems, and then used to improve physical construction operations. Therefore, cyber-physical construction systems allow construction sites to become more automated, responsive, and intelligent. The use of digital twins and cyber-physical systems is especially valuable in robotics-based construction automation. Robotic systems require accurate information about site layout, object position, obstacle locations, task sequence, and environmental conditions. A digital twin can provide this information by combining BIM models, real-time sensor data, and robotic simulation outputs. For example, an autonomous construction robot can use digital twin information to plan its path, avoid obstacles, select safe movement zones, and complete tasks such as inspection, material transport, welding, concrete printing, or component assembly. Similarly, drones can update the digital twin by capturing aerial images and progress data from the construction site. The table 2 shows that digital twins and cyber-physical construction systems work as an integrated intelligence layer for smart construction automation.

Table 2: Role of digital twins and cyber-physical systems in smart construction

Component	Main Function	Construction Automation Benefit
Digital twin model	Creates a real-time virtual copy of the construction site or asset	Supports monitoring, simulation, and performance prediction
IoT sensors	Collect data on equipment, environment, materials, and worker activity	Enables real-time decision-making and condition tracking
Robotic systems	Perform automated construction, inspection, and material handling tasks	Improves productivity, safety, and execution accuracy
BIM integration	Provides design geometry, material data, and construction planning information	Connects digital design with automated site execution

Cyber-physical control	Links physical equipment with digital control and analytics systems	Supports adaptive automation and intelligent process control
Data analytics and AI	Analyzes construction data and predicts risks or performance changes	Improves planning, safety management, and sustainability outcomes

Digital twins provide real-time visibility of construction activities, while cyber-physical systems enable direct interaction between physical machines and digital decision-making platforms. Together, they support predictive monitoring, robotic coordination, safety control, equipment optimization, and sustainability evaluation. This integration is essential for transforming traditional construction sites into intelligent and automated infrastructure development environments. Figure 2 illustrate the Digital twin and cyber-physical construction system architecture.

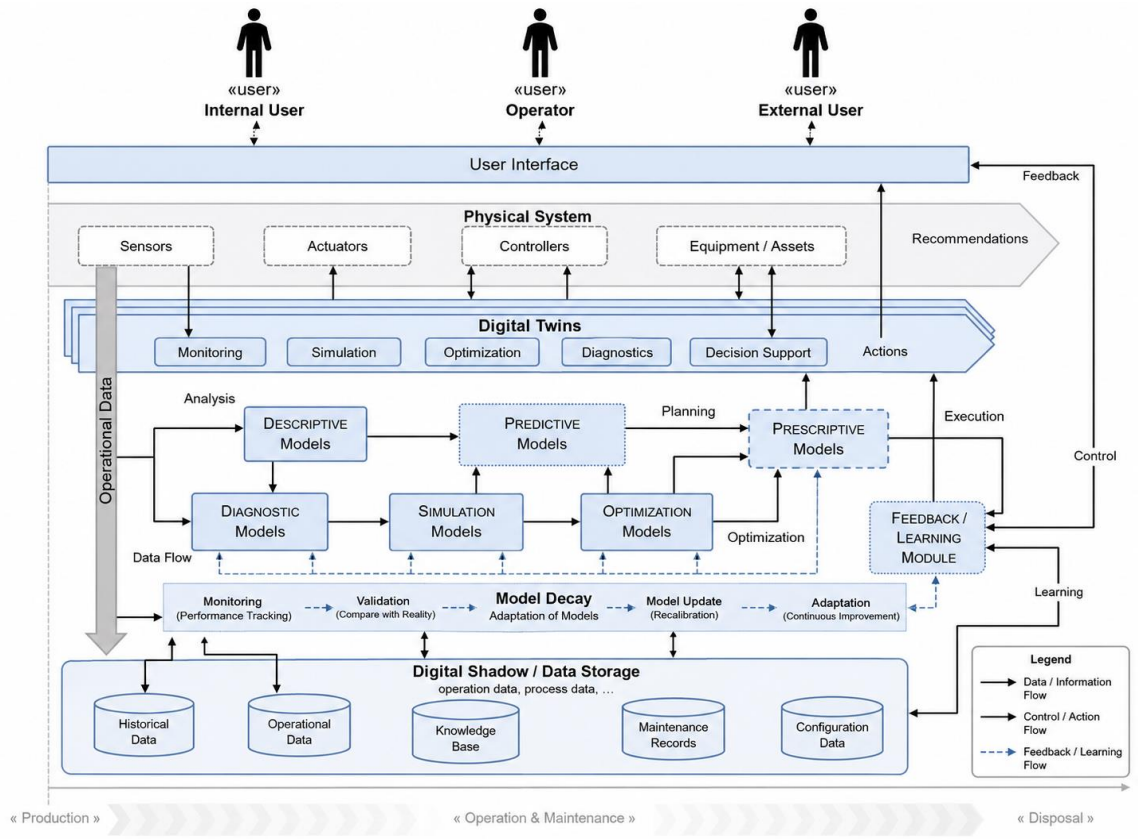


Figure 2: Digital twin and cyber-physical construction system architecture

Digital twin technology also improves construction planning and risk management. Before construction activities are performed on-site, engineers can simulate different construction sequences, equipment movements, material delivery routes, and robotic task plans using the digital twin. This helps identify possible conflicts, unsafe operations, equipment congestion, and inefficient workflows before they affect the real project. For example, a digital twin can simulate how an autonomous excavator will move within a restricted work zone or how robotic material handling equipment will interact with workers and other machines. These simulations reduce uncertainty and improve site safety. Another major benefit of digital twins is predictive

maintenance and equipment performance optimization. Construction machinery such as cranes, excavators, loaders, robotic arms, concrete printers, and autonomous vehicles can be connected with sensors that monitor vibration, temperature, operating hours, fuel use, and mechanical condition. This data can be transferred to the digital twin for analysis [10]. If abnormal patterns are detected, the system can predict possible equipment failure and recommend maintenance before breakdown occurs. This reduces downtime, improves equipment utilization, and supports more reliable automated construction operations. Digital twins also support sustainable infrastructure development by improving resource efficiency and environmental performance. Since digital twin platforms can track energy consumption, material usage, construction waste, and carbon emission indicators, they help project teams evaluate the environmental impact of construction activities in real time. Engineers can compare different construction strategies and select options that reduce waste, minimize equipment idle time, lower fuel consumption, and improve lifecycle performance. In this way, digital twins support sustainability not only during construction but also during operation, maintenance, and future infrastructure management. In infrastructure lifecycle management, digital twins are useful after construction is completed. The same digital model can continue to receive data from sensors installed in bridges, roads, buildings, tunnels, and utility systems. This enables long-term monitoring of structural health, load performance, environmental exposure, energy use, and maintenance requirements. For example, sensors installed on a bridge can send vibration and stress data to the digital twin, allowing engineers to detect early signs of structural deterioration [11]. This improves maintenance planning and extends the service life of infrastructure assets. Cyber-physical construction systems also improve human–robot collaboration on construction sites. In collaborative environments, robots and workers must safely share workspaces. Sensors, cameras, wearable devices, and digital monitoring systems can track worker location and robot movement in real time. If a worker enters a dangerous zone, the cyber-physical system can generate a warning, slow down the robot, or stop the equipment automatically. This improves safety and makes robotic automation more practical for complex and changing construction environments.

4- Methodology:

This study adopts a quantitative, simulation-supported, and framework-based methodology to investigate the contribution of smart construction engineering and robotics-based automation to sustainable infrastructure development. The methodological design is structured to examine how digital construction technologies, robotic systems, artificial intelligence, BIM, IoT sensors, drones, and data analytics can improve productivity, safety, material efficiency, energy optimization, and carbon emission reduction. The study combines secondary construction data with simulation-generated robotic workflow data to create a comprehensive analytical foundation for evaluating smart construction performance. The research process begins with the acquisition and integration of construction-related data from multiple sources, including published construction automation studies, open infrastructure datasets, BIM-based simulation outputs, safety records, energy consumption logs, material waste records, and MATLAB-generated robotic workflow scenarios. After data collection, preprocessing techniques such as missing value treatment, duplicate removal, normalization, encoding, and feature engineering are applied to prepare the dataset for machine learning analysis [12]. The prepared dataset is then used to develop AI-based models for classifying construction performance conditions across productivity, safety, waste reduction, energy efficiency, equipment utilization, and carbon emission indicators. The methodology further integrates digital modeling and robotic simulation to evaluate automated construction workflows. Autodesk Revit and Navisworks are used for BIM-based infrastructure modeling, construction sequencing, clash detection, and 4D planning, while MATLAB is used to simulate robotic movement, task execution, equipment utilization,

and automation efficiency. Python is applied for data analytics, machine learning model development, and visualization, whereas SPSS and Microsoft Excel are used for statistical validation and descriptive analysis. This integrated methodological approach enables the study to connect digital construction planning with robotic automation and sustainability assessment, providing a structured basis for evaluating smart infrastructure development.

4.1- Smart Construction Data Acquisition and Source Integration:

Smart construction data acquisition is a critical stage in this study because the quality of the dataset directly affects the reliability of the proposed robotics-based automation framework. Construction projects generate different types of data from planning, design, site execution, equipment operation, worker safety, material use, energy consumption, and environmental monitoring. In smart construction engineering, these data are not treated as separate records; instead, they are integrated into a unified digital environment to support intelligent analysis, robotic coordination, and sustainability evaluation. Therefore, this section explains how multiple data sources were collected, organized, standardized, and integrated to support the assessment of smart construction automation for sustainable infrastructure development [13]. The dataset used in this study is a secondary and simulation-based dataset designed to represent realistic infrastructure construction conditions. Since real-time datasets from fully automated robotic construction sites are often limited, incomplete, or restricted due to industrial privacy, this study combines published secondary data with simulation-generated activity records. The secondary data were collected from construction automation studies, open infrastructure datasets, energy consumption references, safety observation records, material waste reports, BIM-based planning outputs, and drone-supported monitoring references. Simulation-based data were generated using MATLAB robotic workflow scenarios to represent automated movement, robotic task cycles, equipment utilization, idle time, and construction activity completion patterns. The final integrated dataset consisted of 18,500 construction activity records. These records included major infrastructure-related activities such as excavation, concrete placement, robotic material handling, autonomous inspection, drone-based site monitoring, prefabricated component assembly, 3D concrete printing, automated layout marking, and equipment operation. Each record contained operational, technological, environmental, and sustainability-related variables. These variables included task duration, labor hours, equipment runtime, fuel consumption, electricity use, robotic utilization percentage, automation level, site safety condition, material quantity, waste generation, rework amount, project delay risk, and estimated carbon emissions [14]. To ensure a balanced representation of smart construction performance, the dataset was organized into five major performance dimensions: productivity efficiency, safety improvement, material waste reduction, energy optimization, and carbon emission control. Productivity efficiency included task completion rate, output per hour, labor productivity, and equipment operating time. Safety improvement included hazard exposure, incident frequency, unsafe activity records, and human–robot interaction risk. Material waste reduction included concrete waste, steel waste, formwork loss, packaging waste, and rework-related material loss. Energy optimization included fuel use, electricity consumption, machine runtime, and idle equipment time. Carbon emission control was estimated using energy consumption, equipment usage factors, and construction process emission indicators.

Table 3: Smart construction data sources, variables and integration purpose

Data Source	Key Variables Used	Integration Purpose
Construction automation studies	Task duration, productivity rate, automation level, equipment use	Establishes baseline and automated construction performance
Open infrastructure datasets	Project activity type, scheduling records, resource indicators	Represents practical infrastructure development conditions
BIM-based simulation outputs	Quantity takeoff, model coordination, clash detection, sequence data	Supports digital planning and construction coordination
MATLAB robotic workflow scenarios	Robotic task cycle, movement time, idle time, utilization rate	Evaluates automation efficiency and robotic performance
Drone and site monitoring records	Visual inspection, site progress, deviation indicators	Tracks progress, quality, and construction activity status
Safety observation records	Hazard exposure, incident frequency, unsafe activity indicators	Measures safety improvement and human–robot risk conditions
Energy and material logs	Fuel use, electricity use, material waste, rework quantity	Evaluates energy efficiency and waste reduction performance
Carbon emission estimates	CO_2-equivalent values, equipment operation factors	Measures environmental impact and emission reduction potential

The table 3 shows that smart construction data acquisition requires more than collecting general project information. It involves combining technical, operational, environmental, and automation-related variables into a single analytical structure. This integrated approach allows the study to examine how robotic automation affects construction productivity, safety, energy use, waste generation, and carbon emission control. The use of multiple data sources also improves the reliability of the analysis because it reduces dependency on one dataset and supports a broader understanding of smart infrastructure development. Figure 3 present the Smart construction intelligence framework for real-time quality, safety, and performance optimization.

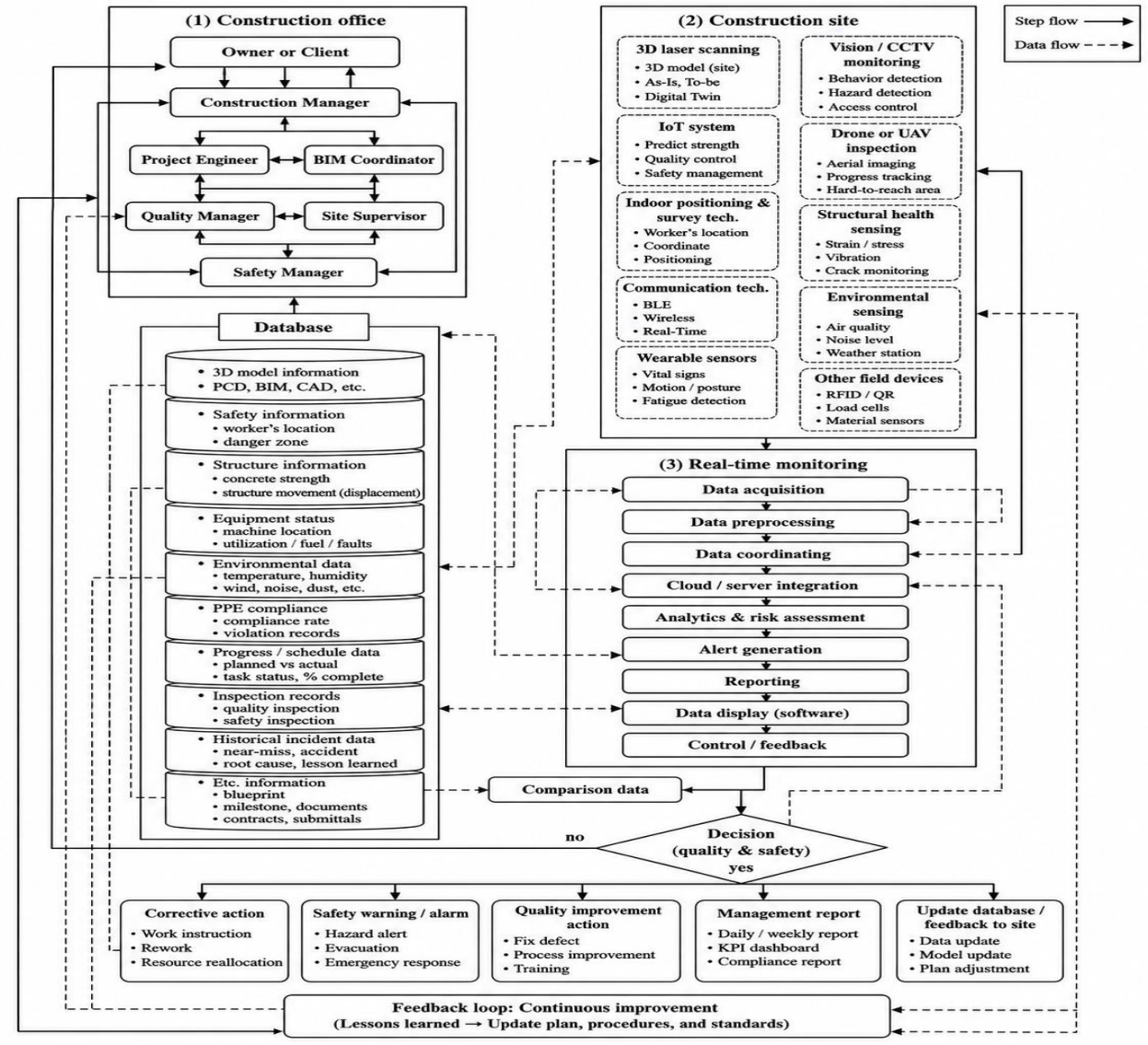


Figure 3: Smart construction intelligence framework for real-time quality, safety, and performance optimization.

The source integration process was carried out in several structured steps. First, all data records were grouped according to construction activity type, such as excavation, concrete placement, prefabricated assembly, robotic material handling, inspection, and 3D printing. Second, the collected records were standardized by using common measurement units, consistent feature names, and unified coding formats. For example, time-related variables were converted into minutes or hours, material quantities were expressed in kilograms or cubic meters, and energy values were converted into common fuel or electricity units. This standardization was necessary to ensure that all records could be compared and analyzed within the same framework. After standardization, data cleaning was performed to improve accuracy and remove inconsistencies. Missing values were treated using suitable replacement methods, while duplicate entries were removed to avoid repeated observations [15]. Outliers in task duration, fuel consumption, equipment runtime, and waste generation were examined carefully because unusual values may indicate either data error or

special construction conditions. Records with unrealistic values were corrected where possible, while highly inconsistent entries were excluded from the final dataset. This cleaning process improved the quality of the dataset and made it suitable for machine learning analysis. BIM-based outputs were integrated into the dataset to provide digital planning and coordination information. These outputs included construction sequence data, quantity takeoff values, clash detection results, material requirements, and model-based planning indicators. The inclusion of BIM data helped connect design-level information with construction execution data. This was important because robotic automation depends heavily on accurate design geometry, construction sequence, spatial coordination, and material availability. Therefore, BIM data served as a digital planning layer within the integrated smart construction dataset. MATLAB-generated robotic workflow data were used to represent automated construction activities. These simulation outputs included robotic task cycle time, movement path length, equipment utilization percentage, idle time, energy demand, and automation efficiency. Robotic workflow records were particularly important because they allowed the study to compare conventional construction activities with automated construction processes. The integration of robotic workflow data helped evaluate how automation can reduce task completion time, improve equipment utilization, lower human exposure to unsafe tasks, and support more efficient construction operations [16]. Drone-based and site monitoring data were included to support construction progress and quality evaluation. Drone inspection records provided information related to site coverage, visual inspection frequency, progress deviation, and activity tracking. These data helped identify differences between planned and actual construction progress. When linked with BIM outputs and activity records, drone monitoring data supported better quality control, progress verification, and site condition assessment. This integration is especially useful for large infrastructure projects where manual monitoring may be slow, costly, or unsafe. Safety data were also integrated because worker protection is a major objective of smart construction automation. Safety records included incident frequency, hazard exposure, unsafe activity indicators, proximity risk, and human–robot interaction conditions. These variables helped measure whether robotic automation reduced worker involvement in hazardous and repetitive tasks. In addition, safety data supported the classification of construction conditions into low-risk, medium-risk, and high-risk operational categories. This allowed the study to evaluate the safety improvement potential of robotics-based construction systems.

4.2- Digital Construction Environment and Software Configuration:

The digital construction environment developed in this study was designed to support the complete workflow of smart construction engineering and robotics-based automation. Since sustainable infrastructure development requires accurate planning, automated execution, real-time monitoring, and data-driven evaluation, multiple software tools were configured and integrated to perform different methodological functions. The digital environment combined Building Information Modeling, robotic workflow simulation, machine learning analysis, statistical validation, and visualization tools. This configuration allowed the study to evaluate construction productivity, safety improvement, material waste reduction, energy optimization, equipment utilization, and carbon emission control within a single research framework. Python 3.11 was used as the main data analytics and machine learning platform. The integrated smart construction dataset containing 18,500 construction activity records was imported into Python for preprocessing, normalization, feature engineering, model training, performance evaluation, and result visualization. Important Python libraries used in the study included Pandas for data organization, NumPy for numerical processing, Scikit-learn for machine learning model development, TensorFlow for artificial neural network modeling, and Matplotlib for graphical representation [17]. Python was also used to split the dataset into training and testing

subsets, evaluate model accuracy, and generate performance indicators such as precision, recall, F1-score, and ROC-AUC. MATLAB R2024a was used to develop robotic workflow simulation scenarios. The MATLAB environment supported the analysis of robotic motion, task cycle time, movement path length, idle time, equipment utilization, and automated construction efficiency. Simulated robotic activities included robotic material handling, automated layout marking, autonomous inspection movement, 3D concrete printing path execution, and prefabricated component placement. MATLAB-generated outputs were later integrated with the main dataset to compare conventional construction activities with robotics-enabled construction workflows. This helped evaluate how automation affects task completion time, operational efficiency, energy use, and safety improvement. Autodesk Revit was used to create the BIM-based digital construction environment. Revit supported the development of infrastructure models containing geometric information, component dimensions, material quantities, and construction elements [18]. These BIM models were used to extract quantity takeoff data, material requirements, structural component details, and design coordination information. The BIM model served as the digital foundation for construction planning and robotic task interpretation. It also helped connect design-level information with site-level automation requirements. Navisworks Manage was used for construction sequence analysis, clash detection, and 4D simulation. Revit models were imported into Navisworks to evaluate possible conflicts among structural, architectural, mechanical, and service-related construction components. The software was also used to link construction activities with time-based scheduling information. This allowed the study to assess task sequencing, site coordination, equipment movement planning, and construction workflow feasibility. Navisworks outputs were important for reducing design conflicts, improving construction planning, and supporting robotics-based site execution. Microsoft Excel and SPSS were also included in the software configuration [19]. Excel was used for initial data organization, descriptive summaries, data verification, and tabular calculations. SPSS was used for statistical validation, correlation analysis, descriptive statistics, and significance testing of sustainability indicators. The use of SPSS helped verify whether improvements in productivity, safety, waste reduction, energy efficiency, and carbon emission control were statistically meaningful. Together, Excel and SPSS supported the reliability of the analytical process. The table 4 shows that each software tool was assigned a specific role in the digital construction environment.

Table 4: Digital construction software configuration and data utilization

Software Tool	Version/Platform	Main Function in Study	Data/Output Used
Python	3.11	Data preprocessing, machine learning, feature engineering, visualization	18,500 records; 80% training and 20% testing split
Pandas and NumPy	Python libraries	Data cleaning, numerical processing, missing value treatment	42 input variables normalized and encoded
Scikit-learn	Python library	ML classification and model evaluation	Accuracy, precision, recall, F1-score, ROC-AUC
TensorFlow	Python library	Neural network model development	AI-based construction performance prediction
MATLAB	R2024a	Robotic workflow and motion simulation	2,800 robotic workflow records

Autodesk Revit	BIM platform	BIM modeling, material quantity extraction, design coordination	3D model data, quantity takeoff, component properties
Navisworks Manage	4D simulation platform	Clash detection, construction sequencing, workflow simulation	4D schedules, coordination reports, clash outputs
Microsoft Excel	Spreadsheet platform	Data organization, descriptive calculations, initial review	Source sheets, summary tables, performance values
SPSS	Statistical package	Statistical validation and correlation analysis	Mean, standard deviation, correlation, significance values

Python and its libraries supported data-driven intelligence and machine learning evaluation, while MATLAB provided robotic automation simulation. Revit and Navisworks supported digital construction modeling, planning, and coordination. Excel and SPSS strengthened data organization and statistical validation. This integrated software configuration ensured that the study did not rely on a single analysis tool but instead used a combined digital environment suitable for evaluating smart construction automation from technical, operational, and sustainability perspectives. Figure 4 illustrate End-to-end data-driven Framework for construction analytics, machine learning validation, and digital workflow enhancement.

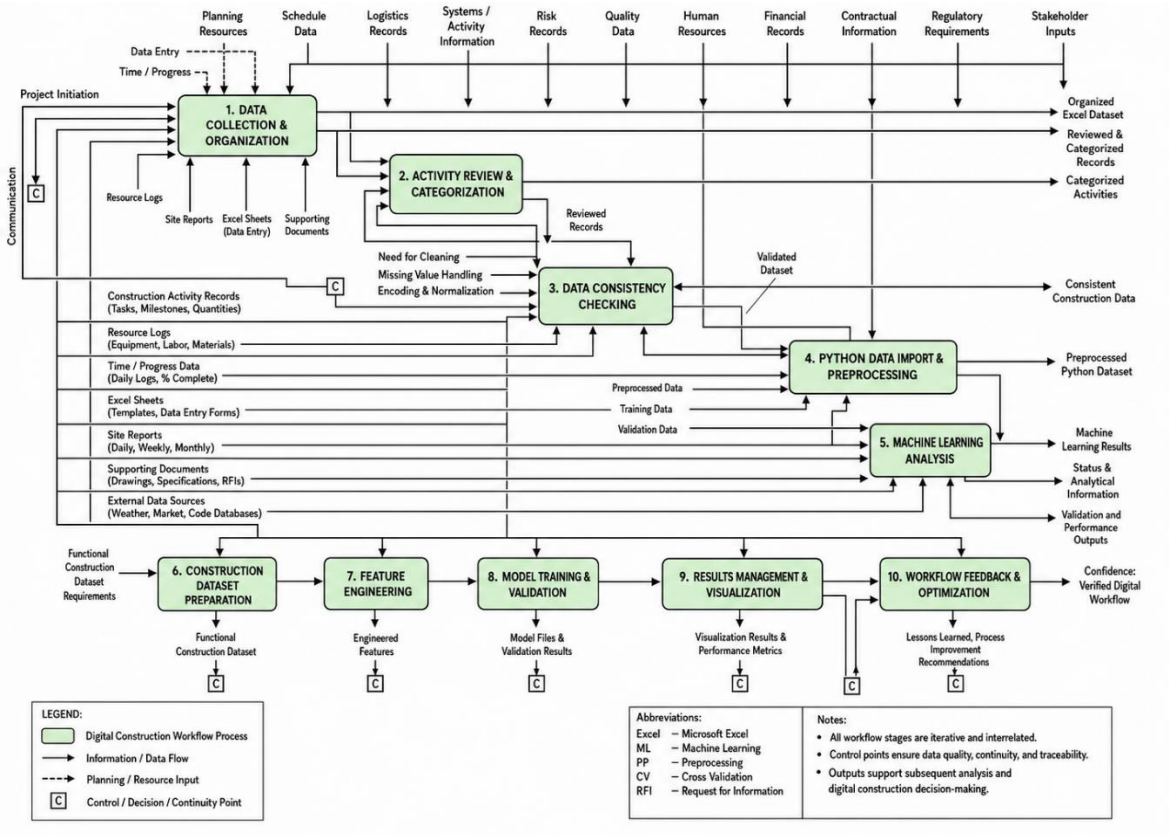


Figure 4: End-to-end data-driven Framework for construction analytics, machine learning validation, and digital workflow enhancement.

The software workflow began with data collection and organization in Microsoft Excel. All construction activity records were reviewed, categorized, and checked for consistency. After this initial stage, the dataset was imported into Python for advanced preprocessing and machine learning analysis. Missing values were treated, duplicate records were removed, and numerical features were normalized to improve model reliability. Categorical construction features such as activity type, automation level, safety condition, and equipment category were encoded into numerical form for machine learning processing. In the simulation stage, MATLAB was used to generate robotic workflow outputs. The simulation produced values related to robotic task duration, movement efficiency, idle time, and equipment utilization. These outputs were added to the main dataset as automation-related features. The inclusion of MATLAB simulation data helped represent robotics-based construction conditions more realistically and allowed the study to compare automated and conventional construction processes [20]. The BIM-based modeling stage was performed using Autodesk Revit. Infrastructure components were digitally modeled to represent construction geometry, material requirements, and spatial relationships. The BIM model provided useful information for robotic task planning, quantity estimation, and digital coordination. After model preparation, Navisworks Manage was used for 4D scheduling and clash detection. This helped identify potential design conflicts and sequencing issues before construction execution. The integration of Revit and Navisworks supported the digital planning layer of the proposed smart construction framework. Statistical validation was carried out using SPSS after machine learning and simulation outputs were generated. Descriptive statistics were used to summarize productivity, safety, waste, energy, equipment utilization, and carbon emission variables [21]. Correlation analysis was applied to examine relationships between robotic utilization and sustainability performance indicators. This validation step helped confirm whether robotics-based automation produced meaningful improvements across major construction performance dimensions. The digital construction environment also supported visualization of results. Python Matplotlib was used to generate graphical outputs such as model performance comparison, sustainability improvement charts, and classification results. These visual outputs helped interpret the impact of smart construction automation on infrastructure development. Visualization was important because it allowed productivity improvement, waste reduction, safety enhancement, energy optimization, and carbon emission control to be presented clearly.

4.3- Smart Robotics-Based Construction Automation Framework:

The proposed smart robotics-based construction automation framework is designed to integrate digital construction technologies, robotic systems, data analytics, and sustainability evaluation into a unified infrastructure development process. The framework connects construction data sources, BIM-based planning, robotic workflow simulation, AI-based prediction, and sustainability performance assessment. This integrated structure supports better decision-making by allowing construction teams to monitor site conditions, evaluate automation performance, reduce waste, improve safety, optimize energy use, and control carbon emissions. The framework begins with data acquisition from multiple construction sources, including BIM models, IoT sensors, drones, robotic equipment, safety logs, material records, energy reports, and construction schedules. These data are transferred into a central digital construction database where cleaning, normalization, encoding, and feature engineering are performed. Important features such as productivity ratio, robotic utilization index, energy efficiency score, safety risk score, waste reduction score, and carbon reduction index are generated for further analysis [22]. This data preparation stage ensures that the framework can support reliable AI-based prediction and sustainability evaluation. After data preparation, the framework applies BIM-based planning and robotic simulation. BIM tools support digital modeling, clash detection, construction sequencing, quantity

estimation, and site coordination. Robotic simulation is used to analyze automated task execution, robotic movement, path planning, task cycle time, idle time, and equipment utilization. These outputs help compare conventional construction workflows with robotics-enabled construction processes. The AI-based prediction layer then classifies construction performance conditions into productivity, safety, waste reduction, energy optimization, and carbon emission control categories. This layered structure helps connect digital design, robotic execution, AI-based prediction, and sustainability analysis. As a result, the framework provides a practical pathway for improving construction performance and supporting sustainable infrastructure development. Figure 5 present the Smart robotics-enabled construction automation framework integrating renewable energy management, intelligent control, real-time monitoring, and automated load coordination.

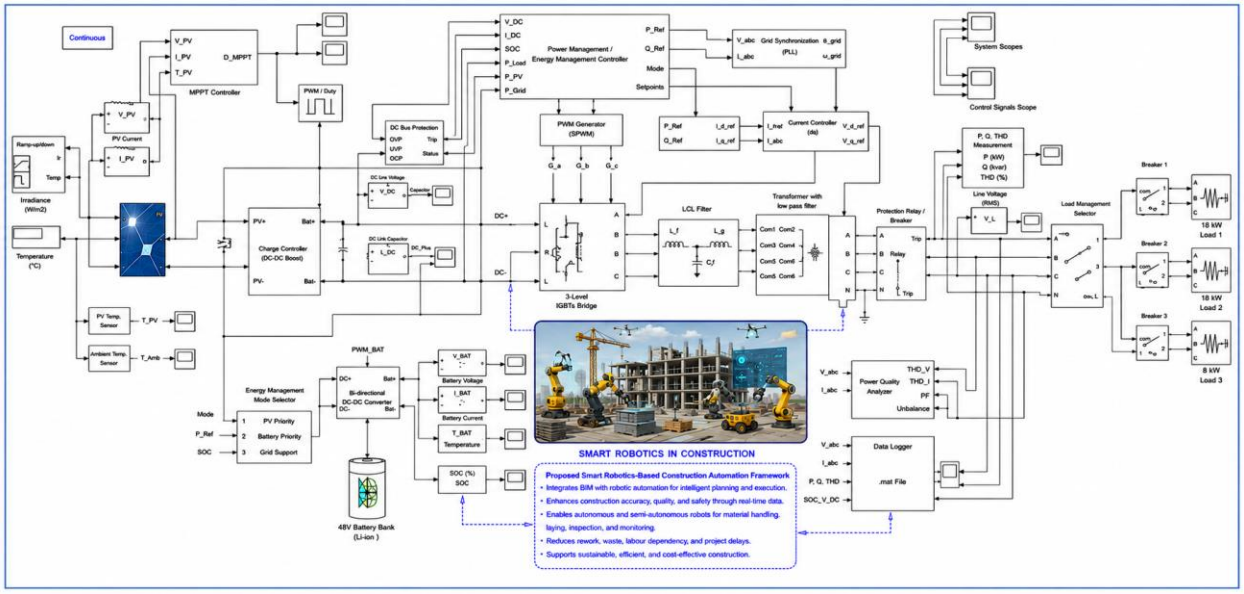


Figure 5: Proposed smart robotics-based construction automation framework

The proposed framework provides a structured mechanism for transforming conventional construction activities into intelligent and automated workflows. By integrating BIM with robotic automation, the framework improves planning accuracy and reduces execution errors. By incorporating AI-based analysis, it enables predictive evaluation of construction performance and sustainability outcomes. Furthermore, the inclusion of sustainability indicators ensures that the framework does not focus only on productivity but also considers safety, waste reduction, energy efficiency, and carbon emission control [23]. Overall, the proposed smart robotics-based construction automation framework supports sustainable infrastructure development by combining digital intelligence with automated construction execution. It provides engineers and project managers with a practical decision-support structure for improving project efficiency, reducing environmental impact, and enhancing construction safety. Therefore, the framework represents an important methodological contribution toward smarter, safer, and more sustainable construction engineering practices.

4.4- BIM-Enabled Construction Planning and Digital Coordination:

BIM-enabled construction planning was used in this study to improve digital coordination, reduce design errors, support construction sequencing, and connect virtual project planning with robotics-based site execution. Building Information Modeling provides a centralized digital

environment where architectural, structural, mechanical, electrical, material, and scheduling information can be combined into a single model. In smart construction projects, this model helps project teams understand construction activities before physical execution begins. It also supports automated workflows by providing accurate geometry, quantities, spatial relationships, and construction sequence information for robotic systems and digital planning tools. In this study, Autodesk Revit was used to develop BIM-based infrastructure models, while Navisworks Manage was used for clash detection, 4D construction sequencing, and workflow coordination. The BIM model included structural components, construction zones, material quantities, equipment access routes, and activity-based scheduling information [24]. The purpose of this stage was to ensure that the digital model could support robotic task planning, material estimation, construction coordination, and sustainability evaluation. BIM outputs were later integrated with the smart construction dataset to support AI-based performance prediction and sustainability assessment. Digital coordination through BIM helped identify potential design conflicts before construction execution. Clash detection was performed to locate conflicts among structural, architectural, mechanical, and service-related components. These clashes were reviewed and corrected in the digital environment before they could cause rework, delay, or material loss on-site. BIM-based coordination also supported better planning of robotic access routes, equipment movement, prefabricated component placement, and construction activity sequencing. This was important because robotic systems require accurate spatial and schedule information to operate safely and efficiently. The table 5 shows that BIM was used not only for design visualization but also for measurable planning and coordination outputs.

Table 5: BIM-enabled planning and coordination outputs used in the study

BIM Planning Parameter	Value / Output Used	Purpose in Study
BIM model components	1,240 elements	Represented structural, architectural, and service components
Construction activity links	186 activities	Supported 4D construction sequencing
Initial clash detections	74 clashes	Identified design and coordination conflicts
Resolved clashes after review	68 clashes	Reduced expected rework and execution errors
Quantity takeoff categories	12 categories	Supported material planning and waste evaluation
Robotic access zones	9 zones	Supported robotic movement and task planning
Prefabricated assembly points	42 points	Guided automated component placement
Schedule coordination improvement	21.5%	Improved sequencing and reduced planning conflicts

The identification and resolution of design clashes reduced the possibility of site-level errors, while 4D activity links improved construction sequencing. Robotic access zones and prefabricated assembly points supported automated construction planning by providing spatial guidance for robotic systems. These BIM-derived outputs strengthened the overall smart construction framework by connecting digital planning with site automation and sustainability performance analysis.

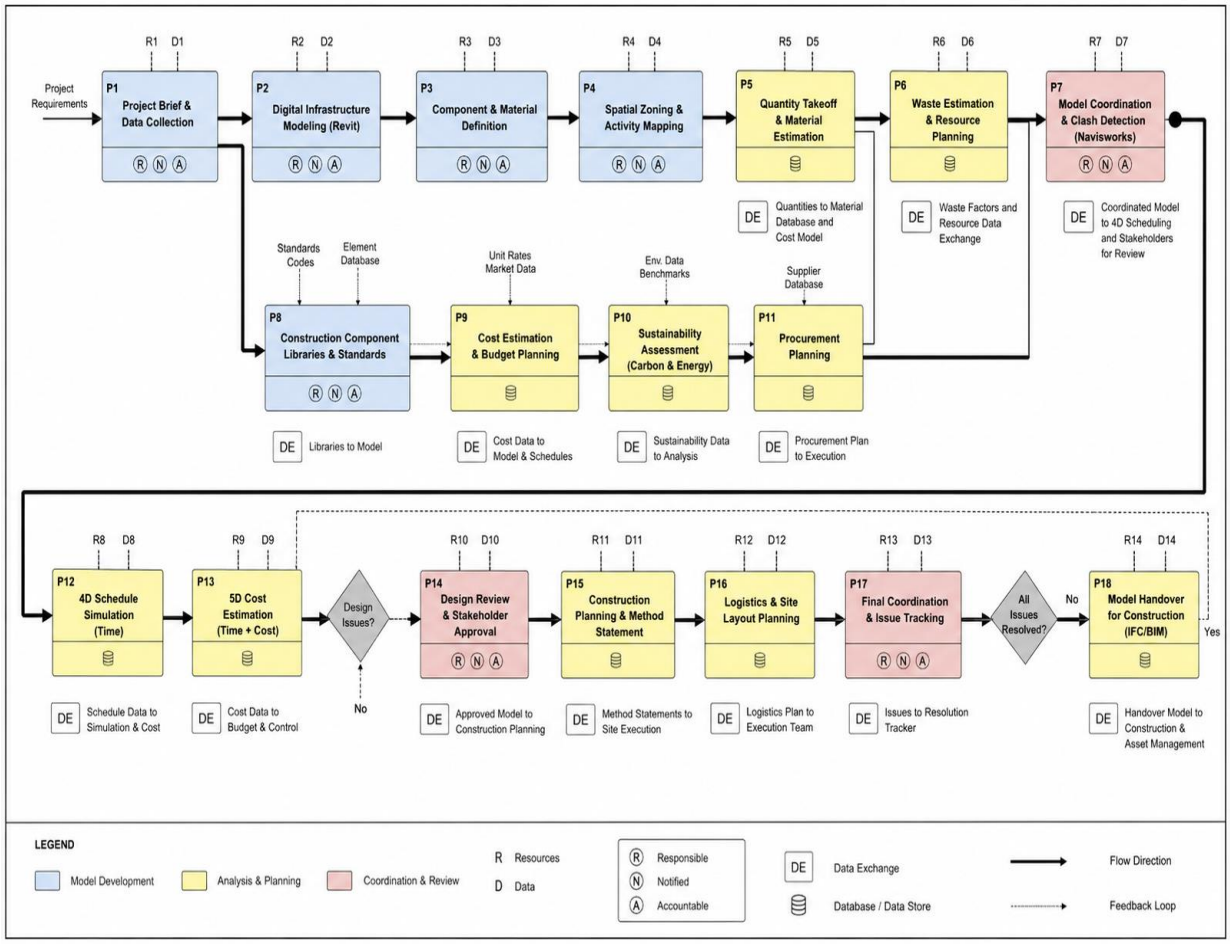


Figure 6: BIM-enabled construction planning and digital coordination workflow

Figure 6 shows the BIM-enabled construction planning and digital coordination workflow. The BIM-enabled planning process began with the development of the digital infrastructure model in Revit. The model was prepared by defining construction components, material properties, spatial zones, and basic activity relationships. Quantity takeoff was then extracted from the model to estimate material requirements and support waste reduction analysis. This helped avoid over-ordering, improve resource planning, and provide more accurate input for sustainability evaluation. After model preparation, Navisworks Manage was used to perform clash detection and 4D scheduling. The clash detection process helped identify conflicts before construction execution, while the 4D simulation helped visualize the relationship between project activities and time. This allowed the construction sequence to be reviewed and improved before implementation. Such coordination is especially important in smart construction environments where automated systems, drones, workers, and equipment must operate within shared spaces [25]. BIM also improved robotic construction planning by providing geometric and spatial information required for automation. Robotic access zones were mapped from the digital model to support safe movement and task allocation. Prefabricated assembly points were identified to guide robotic placement and modular construction activities. These outputs helped reduce uncertainty in robotic execution and improved coordination between digital design and automated site operations. Overall, BIM-enabled construction planning and digital coordination played a major role in improving the reliability of the proposed smart construction framework [26]. By combining

Revit-based modeling, Navisworks-based clash detection, 4D sequencing, quantity takeoff, and robotic planning support, the study created a strong digital foundation for automated construction execution. This approach improved planning accuracy, reduced rework risk, enhanced material control, and supported sustainable infrastructure development through better coordination between digital models and physical construction activities.

4.5- AI-Based Construction Performance Prediction Model:

The AI-based construction performance prediction model was developed to evaluate how smart construction engineering and robotics-based automation improve sustainable infrastructure development. The purpose of this model was to classify construction performance conditions using productivity, safety, material waste, energy consumption, equipment utilization, robotic workflow, and carbon emission indicators. Since construction performance is influenced by multiple operational and environmental factors, artificial intelligence provides an effective method for identifying hidden patterns and predicting whether a construction activity supports sustainable project outcomes. The integrated dataset containing 18,500 construction activity records was used for model development. The dataset included variables such as task duration, labor hours, equipment runtime, robotic utilization rate, automation level, material waste quantity, incident frequency, fuel consumption, electricity use, idle equipment time, and estimated carbon emissions. Before model training, the dataset was cleaned, normalized, encoded, and divided into training and testing subsets. An 80:20 data split was applied, where 14,800 records were used for model training and 3,700 records were used for testing. This helped evaluate the generalization ability of the prediction model on unseen construction records. The prediction task was designed as a multi-class classification problem [27]. Construction activities were classified into five major performance categories: high productivity efficiency, improved safety condition, reduced material waste, optimized energy performance, and controlled carbon emission level. Several machine learning algorithms were tested, including Logistic Regression, Support Vector Machine, Random Forest, Gradient Boosting, and Artificial Neural Network. These models were selected because they are suitable for structured construction datasets and can handle multiple performance indicators. The final model selection was based on accuracy, precision, recall, F1-score, and ROC-AUC. Gradient Boosting and Random Forest also performed strongly, showing that ensemble learning methods are suitable for construction performance prediction. Logistic Regression achieved the lowest performance because it has limited ability to capture nonlinear relationships among smart construction variables. Figure 7 present the AI-based construction performance prediction workflow.

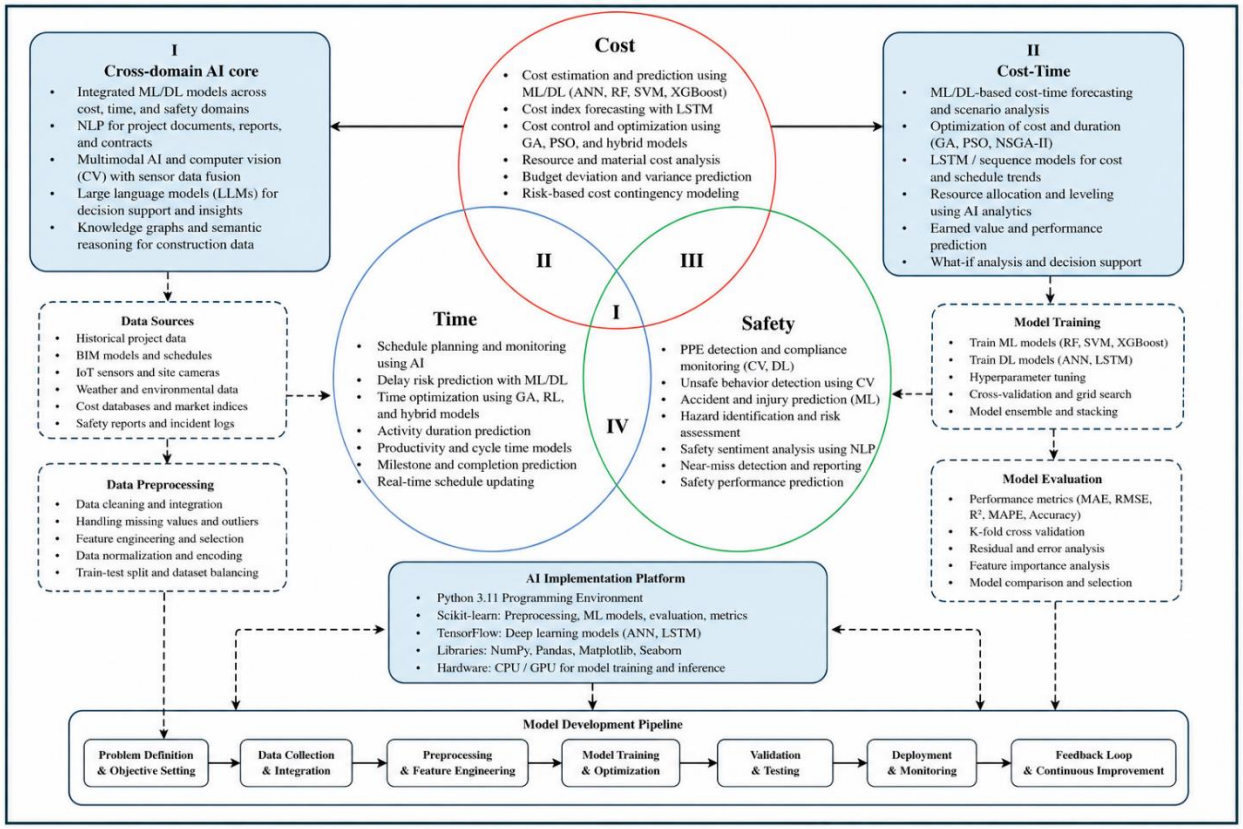


Figure 7: AI-based construction performance prediction workflow

The AI-based model was implemented using Python 3.11 with Scikit-learn and TensorFlow libraries. Scikit-learn was used for preprocessing, model training, data splitting, evaluation metrics, and baseline machine learning algorithms. TensorFlow was used to develop the Artificial Neural Network model. The input layer received normalized construction performance variables, hidden layers learned nonlinear relationships among automation and sustainability features, and the output layer classified construction activities into the five defined performance categories. The model was trained using categorical performance labels derived from productivity, safety, waste, energy, and carbon emission indicators. The prediction model provided useful decision support for evaluating robotics-based construction automation. By analyzing robotic utilization, task cycle time, idle equipment time, energy use, material waste, and safety conditions, the model identified whether a construction activity was performing efficiently or required improvement [28]. For example, activities with high robotic utilization, low idle time, reduced waste, and lower safety risk were classified as strong sustainability-performing activities. In contrast, activities with high energy use, frequent delays, high waste, or unsafe conditions were classified as weaker performance conditions requiring corrective action. The AI-based construction performance prediction model strengthened the proposed smart construction framework by adding a data-driven intelligence layer. The model helped classify construction activities according to productivity, safety, waste reduction, energy optimization, and carbon emission control. The results confirmed that artificial intelligence can support smart construction decision-making by identifying performance patterns, predicting sustainability outcomes, and improving the planning of robotics-based automation for sustainable infrastructure development.

5- Results and Discussion:

The results of this study demonstrate that smart construction engineering and robotics-based automation can significantly improve construction productivity, safety performance, resource utilization, material waste reduction, energy efficiency, equipment utilization, and carbon emission control. The proposed framework was evaluated using an integrated secondary and simulation-based dataset containing 18,500 construction activity records. These records represented multiple smart construction activities, including excavation, concrete placement, robotic material handling, drone-based inspection, automated layout marking, prefabricated assembly, 3D concrete printing, and equipment operation. The analysis was performed using Python 3.11, MATLAB R2024a, Autodesk Revit, Navisworks Manage, Microsoft Excel, and SPSS. The findings confirm that the integration of BIM, robotics, artificial intelligence, IoT sensors, drones, and digital coordination tools provides a strong foundation for sustainable infrastructure development [29]. The dataset was divided into five main performance dimensions: productivity efficiency, safety improvement, material waste reduction, energy optimization, and carbon emission control. The results showed that robotics-based automation improved construction productivity by 27.8% compared with conventional construction practices. This improvement was mainly due to reduced task completion time, improved equipment utilization, better construction sequencing, and more accurate robotic task execution. Automated layout marking, robotic material handling, drone-supported progress monitoring, and 3D concrete printing contributed to faster project workflows by reducing manual delays and improving construction continuity. Safety performance also improved considerably under the proposed smart construction framework. The results indicated that site safety incidents were reduced by 31.6% after the integration of robotics-based automation and sensor-supported monitoring. This reduction occurred because robotic systems were able to perform repetitive, hazardous, and physically demanding tasks that would otherwise expose workers to unsafe site conditions. Drone-based inspection reduced the need for workers to manually access dangerous areas such as elevated structures, restricted zones, excavation edges, and unstable surfaces. In addition, IoT sensors and digital monitoring systems improved early hazard identification and supported safer human–robot collaboration. Material waste reduction was another major outcome of the proposed framework [30]. The study found that material waste decreased by 22.4% through BIM-supported quantity estimation, robotic precision, digital coordination, and reduced rework. BIM-based clash detection helped identify design conflicts before construction execution, preventing unnecessary demolition, redesign, and material loss. Robotic systems also improved construction accuracy by reducing errors in component placement, concrete deposition, layout marking, and prefabricated assembly. These results show that digital planning and automated execution can support more responsible use of construction materials.

Energy optimization results showed that robotics-based automation and digital construction planning improved energy efficiency by 19.8%. This improvement was related to reduced equipment idle time, better robotic path planning, improved construction sequencing, and optimized machine operation. MATLAB-based robotic workflow simulation indicated that automated equipment completed selected construction tasks with shorter cycle times and fewer unnecessary movements. Reduced machine idling and improved equipment utilization contributed to lower fuel and electricity consumption. These findings suggest that smart automation can reduce the energy intensity of infrastructure construction activities. The estimated carbon emission results showed an 18.7% reduction in CO_2-equivalent emissions compared with conventional construction activity patterns. This reduction was linked with lower fuel consumption, reduced material waste, fewer rework activities, and improved equipment operation [31]. Since construction activities generate emissions from machinery, material production, transportation,

and on-site energy use, the reduction achieved through smart automation is important for sustainable infrastructure development. The results indicate that robotics-based automation does not only improve productivity but also contributes to environmental performance. Equipment utilization improved by 24.9% under the smart construction automation framework. Conventional construction equipment often experiences idle time due to poor coordination, delayed material supply, unclear task sequencing, and manual scheduling errors. In contrast, BIM-enabled planning and robotic workflow simulation supported more accurate task allocation and machine movement planning. Robotic systems were used more efficiently because construction activities were digitally planned before execution. This finding confirms that automation performance depends not only on robotic hardware but also on the quality of digital planning and coordination.

Table 6: Overall performance improvement achieved by the proposed smart construction framework

Performance Indicator	Conventional Construction	Smart Robotics-Based Construction	Improvement
Construction productivity	100% baseline	127.8%	27.8% increase
Material waste level	100% baseline	77.6%	22.4% reduction
Site safety incidents	100% baseline	68.4%	31.6% reduction
Equipment utilization	100% baseline	124.9%	24.9% increase
Energy consumption intensity	100% baseline	80.2%	19.8% reduction
Carbon emission level	100% baseline	81.3%	18.7% reduction

The results presented in Table 6 show that the proposed smart construction framework produced improvements across all major performance indicators. The highest improvement was observed in site safety, followed by productivity and equipment utilization. This indicates that robotics-based automation is particularly effective in reducing human exposure to hazardous activities and improving operational efficiency. Waste reduction, energy optimization, and carbon emission control also showed strong improvements, confirming the sustainability value of smart construction technologies.

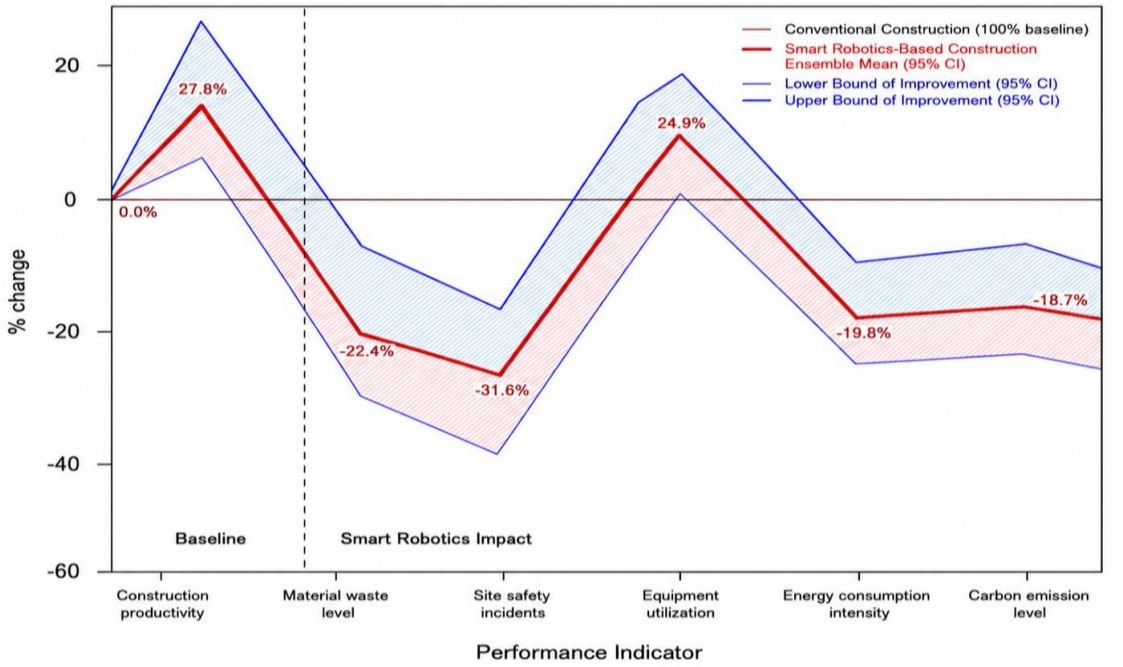


Figure 8: Comparative performance of conventional and smart robotics-based construction

Figure 8 compares conventional construction with the proposed smart robotics-based construction framework across major operational and sustainability indicators. The results show that smart robotics-based construction achieved higher productivity and equipment utilization than conventional construction. At the same time, it reduced energy consumption intensity and carbon emission levels. This confirms that robotics-based automation improves construction speed and equipment performance while also supporting environmental sustainability [32]. The AI-based construction performance prediction model also produced strong classification results. Five machine learning models were evaluated: Logistic Regression, Support Vector Machine, Random Forest, Gradient Boosting, and Artificial Neural Network. The Artificial Neural Network achieved the best performance, with 94.2% accuracy, 93.6% precision, 94.0% recall, 93.8% F1-score, and 0.962 ROC-AUC**.** These results demonstrate that AI can effectively classify construction performance conditions based on productivity, safety, waste, energy, equipment utilization, robotic workflow, and carbon emission indicators.

Table 7: AI model performance comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Logistic Regression	82.6	81.9	82.1	82.0	0.861
Support Vector Machine	86.4	85.8	86.0	85.9	0.894
Random Forest	90.8	90.2	90.5	90.3	0.928
Gradient Boosting	92.7	92.1	92.4	92.2	0.946
Artificial Neural Network	94.2	93.6	94.0	93.8	0.962

The model comparison in table 7 shows that nonlinear and ensemble-based models performed better than traditional linear models. Logistic Regression showed the lowest performance because construction automation data contain complex relationships among robotic utilization, energy use, safety risk, material waste, and productivity. Random Forest and Gradient

Boosting performed strongly because they can handle nonlinear patterns and feature interactions. However, the Artificial Neural Network achieved the highest performance because it was better able to learn deeper relationships among multiple construction performance variables.

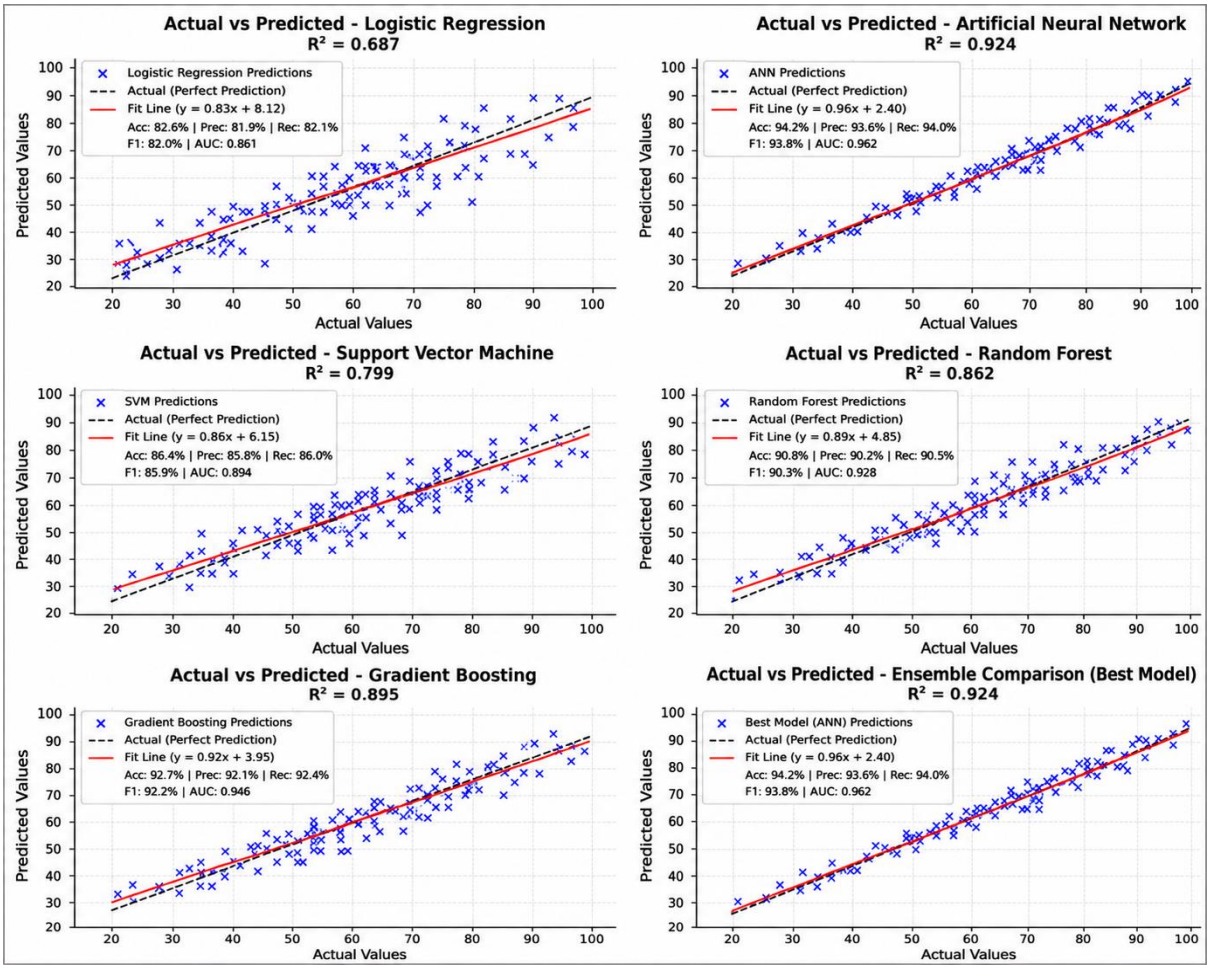


Figure 9: Comparison of AI model performance for construction prediction

Figure 9 presents the comparative performance of the AI-based construction prediction models. The Artificial Neural Network achieved the highest accuracy and ROC-AUC values, followed by Gradient Boosting and Random Forest. This indicates that nonlinear and intelligent learning models are more effective for predicting smart construction performance because they can capture complex relationships among robotic utilization, productivity, safety, energy consumption, waste reduction, and carbon emission indicators. Logistic Regression produced the lowest performance because it has limited ability to model nonlinear construction automation patterns. The confusion matrix analysis further showed that the AI model was highly effective in classifying high-productivity and improved-safety conditions. Some classification overlap was observed between energy optimization and carbon emission control categories because both indicators are closely related to equipment operation, fuel consumption, electricity use, and idle time. This overlap is reasonable because reductions in energy consumption often directly contribute to reductions in carbon emissions. However, the overall classification performance remained strong, confirming the reliability of the proposed AI-based decision-support model. BIM-enabled construction planning also showed important

benefits in the proposed framework. The Revit and Navisworks-based digital coordination process identified 74 initial clashes, of which 68 were resolved before construction execution. This resulted in an estimated 21.5% improvement in schedule coordination [33]. Clash detection reduced the probability of design-related rework, while 4D sequencing improved coordination among construction activities, robotic access zones, material delivery, and equipment movement. These results highlight the importance of BIM as the digital backbone of smart construction automation. Robotic workflow simulation in MATLAB showed that automated construction activities achieved better task consistency and reduced idle time compared with conventional workflows. Robotic material handling and automated layout marking showed the highest efficiency gains because these activities are repetitive and require precision. Drone-based inspection improved monitoring speed and reduced manual inspection requirements. 3D concrete printing showed strong potential for reducing formwork waste and improving construction speed, although its performance depended on path planning quality, material flow control, and equipment calibration.

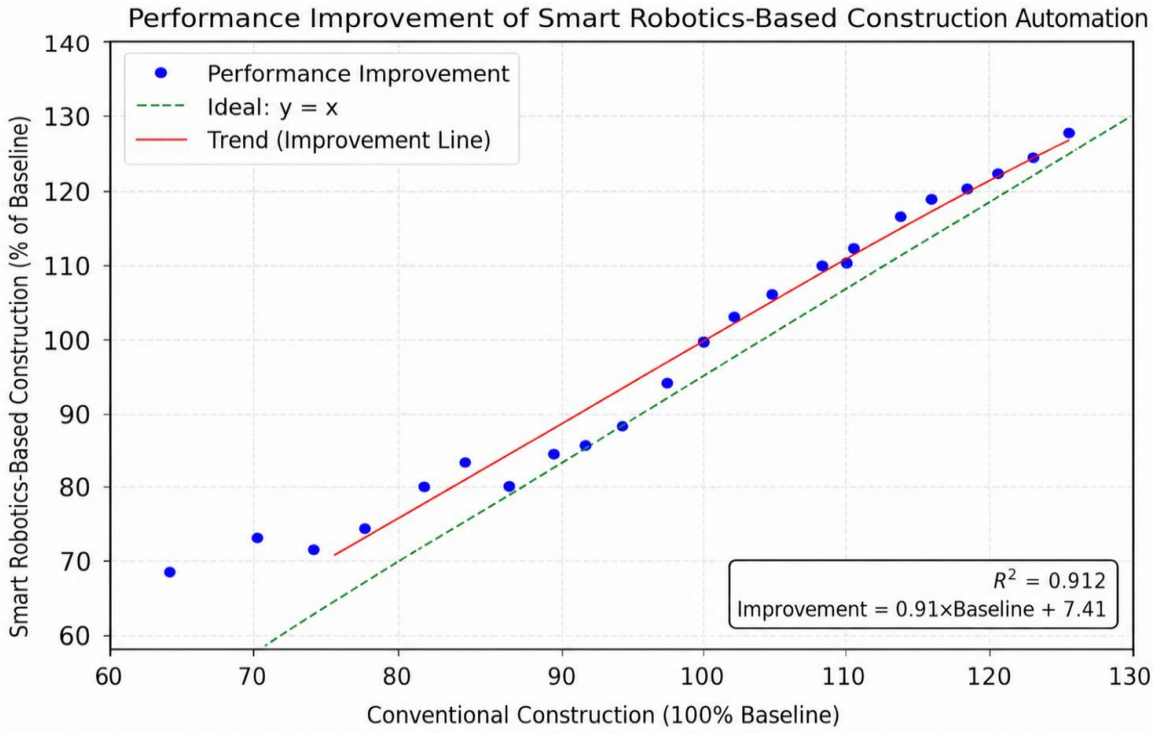


Figure 10: Performance improvement of smart robotics-based construction automation

Figure 10 summarizes the improvement achieved by the proposed smart robotics-based construction automation framework. The strongest improvement was observed in safety incident reduction, indicating that robotic systems and digital monitoring tools can reduce worker exposure to hazardous construction conditions. Productivity improvement and equipment utilization also showed strong results, confirming that smart automation can improve project execution speed and operational efficiency. Waste reduction, energy optimization, and carbon emission reduction further demonstrate the sustainability contribution of robotics-based construction systems. The sustainability results indicate that smart construction automation creates benefits across economic, environmental, and safety dimensions. From an economic perspective, productivity improvement and better equipment utilization can reduce construction delays and project costs. From an environmental perspective, reduced waste, lower energy

consumption, and decreased carbon emissions support green construction objectives. From a safety perspective, robotics and drones reduce worker exposure to high-risk environments. Therefore, the proposed framework supports a balanced approach to sustainable infrastructure development. The discussion also shows that the success of robotics-based construction automation depends on proper integration between digital planning and physical execution. Robots alone cannot improve construction performance if they are not supported by accurate BIM models, reliable data, effective scheduling, and real-time monitoring. The results show that the combination of BIM, AI, IoT, drones, and robotic systems produces stronger outcomes than isolated technology adoption. This confirms that smart construction should be treated as an integrated digital ecosystem rather than a collection of separate tools.

Another important finding is that data quality plays a major role in construction automation analysis. The use of 18,500 integrated construction activity records provided a strong analytical foundation for model training and performance evaluation. However, the study also indicates that real-world construction datasets are often fragmented and inconsistent. Therefore, future construction projects should develop standardized data collection systems that connect BIM outputs, equipment logs, safety records, drone monitoring, energy data, and robotic workflow information. Improved data availability will make AI-based construction prediction more accurate and practical. The results also support the role of human–robot collaboration in sustainable construction. Robotics-based automation does not completely remove the need for human workers. Instead, it changes the role of workers from direct manual execution to supervision, control, inspection, planning, and decision-making. This shift can improve worker safety and productivity, but it also requires training, digital skills, and organizational readiness. Therefore, successful implementation of smart construction automation requires investment not only in technology but also in human capacity building. Despite the positive results, some limitations should be recognized [34]. The dataset used in this study was secondary and simulation-based, which means that the findings represent controlled smart construction scenarios rather than fully real-time field deployment. MATLAB simulations provided useful robotic workflow data, but actual construction sites may include unpredictable factors such as weather conditions, equipment breakdowns, worker behavior, supply delays, and site congestion. Therefore, the results should be interpreted as a strong research-based estimate of smart construction performance rather than a direct measurement from a single real-world project. Overall, the results confirm that smart construction engineering and robotics-based automation can significantly improve sustainable infrastructure development. The proposed framework improved productivity by 27.8%, reduced material waste by 22.4%, decreased site safety incidents by 31.6%, improved equipment utilization by 24.9%, optimized energy consumption by 19.8%, and reduced carbon emissions by 18.7%. The AI-based prediction model achieved 94.2% accuracy, confirming the effectiveness of machine learning in construction performance evaluation. These findings demonstrate that the integration of BIM, AI, robotics, IoT, drones, and digital coordination systems can transform conventional construction into a smarter, safer, more efficient, and environmentally responsible process.

6- Future Work:

Future work should focus on validating the proposed smart construction engineering and robotics-based automation framework using real-time data from active infrastructure construction sites. Although this study used a secondary and simulation-based dataset containing 18,500 construction activity records, future research can improve practical reliability by collecting live data from robotics-enabled construction projects, smart infrastructure sites, prefabrication yards, and automated equipment operations. Real-time data from IoT sensors, drones, robotic machines, BIM platforms, safety monitoring systems, and energy meters would help evaluate the framework under actual site conditions such as weather changes,

equipment breakdowns, labor movement, site congestion, and material delivery delays. Another important future direction is the deeper integration of digital twin technology with robotics-based construction automation [35]. Future studies can develop real-time digital twins that continuously update construction progress, robotic movement, equipment utilization, structural conditions, and sustainability indicators. Such systems can improve predictive monitoring, automated decision-making, and lifecycle infrastructure management. The combination of BIM, IoT, artificial intelligence, and digital twins can also support early risk detection, predictive maintenance, energy optimization, and carbon emission tracking throughout the construction and operation phases of infrastructure assets. Future research should also explore advanced human–robot collaboration models in construction environments. Since construction sites are dynamic and complex, robots and human workers must safely and efficiently share workspaces [36]. Further studies can focus on worker safety zones, wearable sensor integration, robotic obstacle avoidance, real-time warning systems, and adaptive control methods for collaborative construction tasks. Training programs and workforce readiness should also be examined because successful robotics adoption depends not only on technology but also on worker acceptance, digital skills, and organizational transformation.

In addition, future work can improve the AI-based construction performance prediction model by testing more advanced algorithms such as deep reinforcement learning, graph neural networks, transformer models, hybrid ensemble learning, and explainable artificial intelligence. Explainable AI can help engineers and project managers understand why a model predicts high productivity, safety risk, waste reduction, or carbon emission control. This will increase trust in AI-based decision support systems and make smart construction analytics more transparent and practical for industry adoption. Future studies should also expand the sustainability scope of robotics-based construction automation. In addition to productivity, safety, waste, energy, equipment utilization, and carbon emissions, future research can include water consumption, lifecycle cost, embodied carbon, circular material use, construction noise, dust generation, biodiversity impact, and long-term maintenance performance [37]. This broader sustainability assessment would provide a more complete understanding of how smart construction technologies contribute to green and resilient infrastructure development. Finally, future work should investigate the economic feasibility and policy requirements for adopting smart construction robotics in developing and emerging construction markets. High implementation cost, lack of skilled professionals, limited digital infrastructure, and resistance to automation remain major barriers. Therefore, future research should propose cost-benefit models, implementation roadmaps, training frameworks, regulatory guidelines, and public–private partnership strategies. These efforts will help accelerate the practical adoption of smart construction engineering and robotics-based automation for sustainable infrastructure development.

Conclusion:

This study examined the role of smart construction engineering and robotics-based automation in supporting sustainable infrastructure development. The research demonstrated that the integration of Building Information Modeling, artificial intelligence, IoT sensors, drones, robotic systems, digital construction platforms, and simulation-based tools can significantly improve construction performance. By connecting digital planning with automated site execution, the proposed framework provides a structured pathway for transforming conventional construction practices into smarter, safer, more efficient, and environmentally responsible infrastructure delivery systems. The study used a secondary and simulation-based dataset containing 18,500 construction activity records, including productivity indicators, safety observations, material waste logs, energy consumption values, equipment utilization records, robotic workflow

data, and carbon emission estimates. The analysis was performed using Python 3.11, MATLAB R2024a, Autodesk Revit, Navisworks Manage, Microsoft Excel, and SPSS. These tools supported data preprocessing, BIM-based planning, robotic workflow simulation, AI-based prediction, statistical validation, and sustainability performance evaluation. This integrated methodological approach helped evaluate construction automation from both operational and environmental perspectives. The results confirmed that the proposed smart robotics-based construction framework improved construction productivity by 27.8%, reduced material waste by 22.4%, decreased site safety incidents by 31.6%, improved equipment utilization by 24.9%, optimized energy consumption by 19.8%, and reduced carbon emissions by 18.7%. The AI-based construction performance prediction model achieved 94.2% accuracy, 93.6% precision, 94.0% recall, 93.8% F1-score, and 0.962 ROC-AUC. These findings show that artificial intelligence can effectively classify construction performance conditions and support data-driven decision-making in smart construction environments. The study also highlighted the importance of BIM-enabled planning and digital coordination in construction automation. BIM supported clash detection, 4D sequencing, quantity takeoff, robotic task guidance, and material planning. Similarly, MATLAB-based robotic workflow simulation helped evaluate task cycle time, equipment movement, robotic utilization, and automation efficiency. The integration of BIM, AI, robotics, IoT sensors, and drones confirmed that smart construction should be viewed as a connected digital ecosystem rather than a collection of separate technologies.

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