E-ISSN: 1116 - 2759 P-ISSN: 3027-0111
MPRI-EDIR | INTERNATIONAL JOURNAL OF EARTH DESIGN AND INNOVATION RESEARCH
VOL. 11 NO. 4 – JANUARY, 2026

OPTIMIZING PROJECT MANAGEMENT EFFICIENCY THROUGH DIGITAL TWIN-ENABLED PREDICTIVE MAINTENANCE IN SMART BUILDING FACILITY MANAGEMENT

***CHIJIOKE GEORGE EDEH; **FELIX OLUWALOMOLA; ***RUFUS FIDELIS OJUOLUWA; & ****CONFIDENCE ADIMCHI**

*Department of Civil Engineering, Purdue University USA. **Department of Information Systems & Technology, National Open University of Nigeria. ***Department of Quantity Surveying, Moshood Abiola Polytechnic, Abeokuta, Ogun State, Nigeria. ****Chinonyerem, Abia State Polytechnic, Nigeria.
Corresponding Author: edehgeorgec@gmail.com
DOI: https://doi.org/10.70382/mejedir.v11i4.074

Abstract

This research emphasizes designing and testing an intelligent Digital Twin framework that will increase project management efficiency and operational productivity within smart building facility management. The main objective of the system will be to monitor and predict, maintain, optimize energy consumption, and make decisions on energy use. To achieve these objectives, the research method incorporated an end-to-end system design and development process involving architectural modeling, multi-sensor implementation, and data acquisition, with an emphasis on developing an intelligent framework. To build and develop the Digital Twin framework, Message Queuing Telemetry Transport, Hypertext Transfer Protocol, and Modbus were implemented. PostgreSQL, InfluxDB, and SQLite databases were implemented based on data structure and functionality. To develop an end-to-end workflow automation platform, Node-RED programming tools were incorporated. A dynamic interface will be used for

Keywords: Management Efficiency, Digital Twin, Predictive Maintenance, Smart Building, Facility Management.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

visualization and display, which will be directly linked with Power BI. A Long Short Term Memory neural network will be implemented for forecasting and anomaly detection based on energy and environmental data. The findings revealed major enhancements in operational response, situational understanding, and prediction capabilities. The system effectively identified anomalous readings like carbon dioxide levels beyond 600 parts per million, temperature beyond 18-22°C, and humidity beyond 50-80 percent. The Long Short-Term Memory network had a Root Mean Square error value of 0.04, thus signifying efficient prediction. The Digital Twin additionally facilitated better maintenance planning and optimal energy utilization. Overall, the research work represents a scalable and holistic approach that marks progress in intelligent facility management. It integrates sensing, prediction, and visualization capabilities into a single operating environment.

Introduction

Smart building technologies have experienced such fast development that they now reshape the entire process of facility management and engineering work and construction project management for built environments. The worldwide energy usage and operational expenses of buildings require facility management to achieve maximum reliability together with sustainable operations at affordable costs (Serrenho et al., 2023). The current traditional maintenance systems depend on two main approaches which include reactive maintenance and scheduled maintenance based on fixed time intervals (Hamasha et al., 2023). The current maintenance systems experience multiple problems because they cause regular system interruptions and they waste resources while their equipment assets deteriorate. The current need for building management research and practice demands maintenance systems which use intelligent data-driven approaches for anticipatory maintenance (West et al. (2024). The Digital Twin represents a fundamental technological breakthrough which solves enduring challenges that have existed throughout building lifecycle management (Attaran & Celik, 2023). A Digital Twin functions as an always-active digital representation which tracks physical buildings and assets through real-time updates from sensor data and building management systems and environmental monitoring platforms (Iranshahi et al., 2025). The virtual replica enables building operators to observe system conditions while performing simulations for failure prediction and making improved planning choices that span various project management aspects (Jones et al., 2020). Digital Twin systems which integrate with predictive maintenance frameworks represent a leading smart building management trend because they enable facility managers to predict equipment failures and simulate future system behavior for risk assessment and resource optimization

(Hodavand et al., 2025). The combination of predictive maintenance with data-driven modeling and machine learning enables equipment degradation prediction through continuous sensor data collection which produces optimal maintenance schedule forecasts. Digital Twin enabled predictive maintenance in buildings demonstrates its ability to boost system reliability while minimizing operational interruptions according to Lu et al. (2020). The integration of sensor data from heating systems and ventilation and air conditioning and elevator and structural monitoring devices enables facility managers to create performance simulations for assets under different usage scenarios and identify system problems and establish the exact time for maintenance intervention (Osei-Owusu et al., 2025). The predictive system provides better results than traditional manual inspection methods and static maintenance schedules because it helps avoid unneeded maintenance work and prevents expensive system breakdowns.

Research studies now show that Digital Twin-based predictive maintenance systems enhance operational efficiency in buildings while creating major improvements in project management operational efficiency. Smart building projects require ongoing planning activities and scheduling and contractor coordination and budget management and performance tracking and risk management strategies. Research indicates that Digital Twin platforms enhance these operations through their ability to monitor maintenance activities in real time while showing resource status and creating optimized work sequences which reduce task lengths and improve stakeholder communication (Khajavi, Motlagh, Jaribion, & Holmström, 2019). The Digital Twin analytics system delivers enhanced transparency and decision support which enables projects to become more responsive and integrated thus reducing delays while improving cost management and quality standard compliance.

The actual deployment of Digital Twin-based predictive maintenance shows inconsistent results between different geographic areas and various types of buildings. The main obstacle to overcome involves data interoperability because most buildings operate with outdated systems which fail to connect properly with contemporary data management systems (Opoku et al., 2021). The process of creating a complete Digital Twin requires substantial financial resources which become more challenging when working with big buildings that do not have digital documentation available (Ighofiomoni et al., 2025). The development of predictive maintenance models for industrial use has reached maturity but their implementation in building operations remains in development because of the complex environmental factors and building usage patterns and occupant activities. Research studies have identified three main areas of deficiency which include the need for better model interpretability and insufficient personnel with advanced analytics expertise and inadequate data protection systems (Sepasgozar, 2021).

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

The existing problems require experts to develop methodological frameworks which will unite Digital Twin technology with predictive maintenance approaches and project management principles into a single operational system (Pan & Zhang, 2021). The evaluation of predictive maintenance requires these frameworks to assess both its operational success and its effects on project operations and decision-making processes and lifecycle expenses and team member teamwork. Digital Twin adoption will not produce its complete advantages for facility managers because they lack a complete understanding of the system.

Research must immediately focus on studying Digital Twin-based predictive maintenance systems which improve project management performance in smart buildings through empirical and conceptual investigations. The research investigates how Digital Twin systems affect project scheduling precision and resource allocation and budget forecasting and maintenance sequence determination and risk minimization and team communication between different disciplines. The research investigates Digital Twin technology integration with predictive maintenance systems for smart building facility management to determine essential efficiency improvements and deployment challenges and success requirements.

The research results will provide useful information which benefits facility managers and building developers and policy makers and technology providers. They will also support the development of structured guidelines for implementing Digital Twin enabled predictive maintenance systems as a core element of next-generation facility management, aligning with global trends toward sustainable, resilient, and intelligent built environments.

Review of related Literature

Research into building operations through intelligent technologies has grown because Digital Twin systems enable predictive maintenance and enhance managerial efficiency throughout the lifecycle of smart buildings. The research in this field covers four essential topics which include (1) Digital Twin fundamental principles and (2) new predictive maintenance approaches for constructed facilities and (3) Digital Twin applications in smart building operations and (4) Digital Twin effects on project management results. The three research threads deliver vital knowledge about how Digital Twin-based predictive maintenance adoption depends on technological elements and methodological approaches and operational requirements.

The fundamental principles which support digital twin technology

The Digital Twin concept developed from initial engineering studies which used virtual models of physical objects to run simulations and monitor asset life cycles Machacek et

al. (2025), established one of the first essential definitions which described Digital Twins through three core elements which included physical assets and virtual models and their connecting data stream that maintained ongoing synchronization (Iliuță et al., 2024). This created the base which enables Digital Twin systems to operate in complicated engineered systems.

Madni and Madni (2019) developed the conceptual framework through their which showed that Digital Twin systems use real-time analytics and artificial intelligence and cyber–physical interactions to aid operational decision-making (Ogunnowo et al., 2024). This demonstrated that Digital Twin platforms deliver complete situational awareness which makes them ideal for monitoring and prediction-based operations in such environments. Digital Twin systems according to this conceptual framework enable buildings to duplicate their structural elements and mechanical systems and environmental conditions in real-time for better maintenance decision-making (Shahzad et al., 2022). Fuller and his colleagues Fan and Day and Barlow (2020) performed a detailed state-of-the-art assessment which demonstrated that sensor network progress and cloud computing and data integration advancements have created better conditions for Digital Twin implementation in building environments. He also found that Digital Twin adoption in facility management faces ongoing problems with data quality and model scalability and interoperability.

The research provides theoretical foundations which explain how Digital Twin systems function as digital infrastructure for predictive maintenance and project management optimization.

Predictive Maintenance in Built Environments

Predictive maintenance uses data analytics together with condition monitoring technologies to identify when equipment will fail so maintenance can happen before breakdowns occur. The built environment has adopted this concept because modern systems have become more complicated while organizations need to implement preventive maintenance approaches.

The authors Li Deng and Mahadevan (2020) showed that predictive models based on data enable the prediction of building mechanical system component deterioration through the analysis of system operation data and environmental conditions. The research confirmed that predictive maintenance methods help organizations decrease equipment downtime while enhancing their asset reliability standards.

Galar and Kumar (2016) demonstrated that predictive maintenance enables organizations to transition from their current reactive maintenance approach to proactive maintenance which decreases maintenance requirements and prolongs asset operational periods. The research conducted by these authors about industrial systems contains three essential

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

elements which smart buildings can use directly through their work on data integration and sensor-based diagnostic systems and reliability assessment methods. Carvalho and his colleagues Soares Vita and del Real Torres (2021) studied predictive maintenance approaches for heating ventilation and air conditioning systems to prove that machine learning detection models detect problems before human staff members do. Their research demonstrates that predictive maintenance techniques will serve as essential tools to enhance building operational performance and sustainability.

He shows that predictive maintenance has developed into a solid technological field but facility managers still face difficulties when they try to implement this system throughout their entire building management process.

Digital Twin Applications in Smart Building Facility Management

Digital Twin systems integration with smart building management systems has become increasingly popular among scholars. Research exists which studies how Digital Twin platforms improve both real-time monitoring and operational decision-making processes. Khemlani (2020) explained that Digital Twin systems operating within building information modeling environments maintain real-time data about structural systems and their energy performance and mechanical components. The system enables dynamic facility management through its integrated design which provides better diagnostic accuracy and simulation capabilities for different scenarios. Ding Zhou and Akinci (2021) demonstrated how Digital Twin technology enables structural health monitoring through its ability to track performance anomalies which standard monitoring systems cannot detect. Their research demonstrates that Digital Twin systems provide superior benefits for situations which require both safety and reliability. O'Grady and his colleagues Mulholland and Braithwaite (2022) conducted research about Digital Twin deployment in commercial smart buildings which demonstrated that digital models operating in real-time enhanced maintenance operation visibility. Digital Twin systems enable better communication between engineers and technicians and facility managers which results in improved operational efficiency.

Zou Xu and Wang (2023) studied Digital Twin deployment in building operations to find that data integration and interoperability problems continue to block its implementation. The researchers demand better data standards and open frameworks which will enable Digital Twin systems to connect properly with building automation technologies. Digital Twin systems have the ability to generate useful data for facility management but the system faces multiple obstacles which affect its technical operation and data quality and ability to expand.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Project Management Implications of Digital Twin–Enabled Predictive Maintenance

Digital Twin system integration with predictive maintenance produces both technical advantages and managerial effects. Smart building project management requires continuous scheduling and coordination and budget management and resource distribution which smart buildings affect through their performance requirements and maintenance requirements. Shen Hao and Xue (2020) demonstrated that Digital Twin platforms enhance project planning through their ability to perform simulation-based assessments of maintenance operations and resource management and time-related activities. Project managers who use virtual testing methods can identify potential disruptions which enables them to make schedule changes before starting actual construction work. Garcia and his colleagues Valdebenito and Claramunt (2021) in their facility case study demonstrated that Digital Twin systems enhance project coordination through their ability to show current equipment status and maintenance work advancement. Their research demonstrated that organizations achieved shorter decision-making times and their maintenance teams became more effective at communicating with each other while their operational and strategic project targets became more consistent. Braun Wetzstein and Seiger (2022) studied how Digital Twin-based analytics systems enhanced building renovation and maintenance project cost management through their research. The research findings showed Digital Twin systems produced predictive data which enabled project managers to forecast asset deterioration costs thus improving their ability to create precise budget projections. Digital Twin-based predictive maintenance has evolved into an essential project management resource which delivers enhanced operational performance through risk reduction and performance improvement in smart building management.

Project Management Efficiency

The main priority for project management exists in fields which create engineered systems and built environments and deliver complex services. Project management efficiency means organizations should reach their project targets which include scope and time and cost and quality and stakeholder satisfaction while they reduce their consumption of resources and their occurrence of delays and their need for additional work (Turner, 1999). Project management efficiency research has evolved through three decades from using normative frameworks and best practice guides to conducting empirical studies about determinants and measurement methods and digital transformation impacts on project results. The research findings from this study are presented through five connected sections which examine (1) project management efficiency definitions and performance assessment methods and (2) construction and infrastructure project efficiency factors and (3) value-creation models for efficiency

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

measurement and (4) digital technology and data analytics effects on project efficiency and (5) how organizational elements and human aspects influence efficiency improvements.

Definitions and Metrics of Project Management Efficiency

The concept of project management efficiency exists as a specific operational measurement and also as a comprehensive framework which generates value. The first studies about efficiency measured it through the calculation of output to input ratios which represented work results against time and monetary expenses (Kerzner, 2017). Turner (1999) established that project efficiency needs to be evaluated based on specific project conditions because projects must frequently sacrifice one factor for another between their schedule and cost and quality elements. The Project Management Institute (2017) supports modern research which develops composite metrics that unite time adherence with cost variance and quality indices and stakeholder satisfaction to measure efficiency. The composite methods aim to handle project outcome intricacies by using multiple evaluation criteria which surpass the limitations of individual performance indicators. Zwikael and Smyrk (2011) developed this concept by placing project efficiency within organizational value systems which they believed should focus on achieving strategic goals and benefits delivery instead of immediate cost reduction.

Determinants of Efficiency in Construction and Infrastructure Projects

The construction and infrastructure literature contains extensive research which identifies various elements which affect project management operational efficiency. Multiple countries experience ongoing delays together with rising construction expenses and reduced workforce efficiency according to researchers who have found both physical and non-physical factors at play.

Research findings show that design modifications together with weak contract administration and delayed project choices and insufficient planning and missing stakeholder coordination practices lead to project inefficiencies (Odeh & Battaineh, 2002; Sweis, Sweis, Hammad, & Shboul, 2008). Sambasivan and Soon (2007) identified identical project delay factors which they studied in Malaysia. The authors established that three main factors which include resource shortages and delayed contractor payments and unexpected site conditions lead to significant project delays and cost increases. Flyvbjerg and his co-authors Bruzelius and Rothengatter (2003) studied how optimism bias and strategic misrepresentation affect large infrastructure projects which results in underestimating project costs and schedules that negatively impact operational efficiency.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

This show that technical solutions by themselves do not solve the problem. The efficiency of project management depends on three main factors which include governance systems and contractual terms and institutional reward systems that determine how decisions get made and how risks get distributed.

Measurement Models and the Value-Creation Perspective

Project management efficiency measurement has shifted from using baseline plans to measure variance to evaluating how projects create value for the organization. Zwikael and Smyrk (2011) developed a measurement model which links project deliverables to organizational results while recommending performance indicators that show how benefits materialize and affect sustained organizational success.

The Project Management Institute publishes yearly reports which demonstrate that organizations need to track both predictive metrics including schedule performance indices and outcome metrics which include actual benefits delivery and stakeholder contentment (Project Management Institute, 2017). The research by Dvir and Raz and Shenhar (2003) demonstrated that projects which follow strict planning methods and maintain strategic goal alignment will achieve better results and operational efficiency according to the authors who recommend strategic alignment metrics for efficiency assessment.

The different viewpoints demonstrate that project management efficiency requires multiple assessment points throughout the entire project lifecycle to show enduring value instead of focusing on short-term cost or time reductions.

Digital Technologies and Data-Driven Methods: Effects on Efficiency

Digital technology projects has produced a large number of studies which demonstrate their ability to enhance project management operational efficiency. Research on building information modeling and sensor networks and data analytics demonstrates that these systems deliver similar advantages which include better information transparency and enhanced coordination and decreased error rates. Studies about building information modeling show that models which share information between stakeholders help decrease design disagreements while enhancing measurement accuracy and shortening project review periods which results in better schedule and cost outcomes (Azhar, 2011; Eastman, Teicholz, Sacks, & Liston, 2011). Volk Stengel and Schultmann (2014) analyzed building information modeling for existing buildings and demonstrated that digital model integration across building life cycles enables improved maintenance planning and minimizes operational inefficiencies which become apparent during maintenance activities.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Predictive analytics and condition-based maintenance through modeling demonstrates how data analytics helps organizations prevent equipment breakdowns while improving their ability to manage resources effectively. Mobley (2002) established predictive maintenance principles which help organizations decrease their need for emergency shutdowns. Jardine Lin and Banjevic (2006) analyzed machinery diagnostic and prognostic systems which demonstrated that identifying problems at an early stage and calculating equipment lifespan helps organizations decrease their maintenance expenses and prevents equipment breakdowns from causing project delays.

Research conducted during the last few years demonstrates that these abilities create direct benefits for project management operational performance. Project planners can prevent schedule delays through proactive maintenance planning when digital models and real-time sensor data help them predict equipment deterioration. The integrated data-based interventions help organizations achieve reduced work stoppages and better resource management and enhanced contractor collaboration.

The literature shows that technology efficiency depends on three essential factors which include workflow optimization and data precision and system integration. The research by Volk et al. (2014) and Eastman et al. (The authors (2011) demonstrate that technology implementation without process transformation produces minimal organizational advantages because organizations need to dedicate themselves to new operational methods and data management systems to achieve substantial efficiency gains.

Organizational, Human, and Contractual Factors that Moderate Efficiency

This demonstrate that organizational readiness together with stakeholder competence and contractual frameworks determine how technical tools create efficiency improvements. Turner and Keegan (2001) and Kerzner (2017) identify leadership and project governance and skilled personnel as essential factors which support efficient project execution.

The implementation of contractual systems plays an important role in this process. The research by(Gbahabo & Ajuwon, 2017) shows that contract terms together with risk allocation and incentive structures either help reduce inefficiencies or make them worse. The use of contracts which fail to promote teamwork and unclear risk distribution between parties leads to more disputes and opportunistic actions which decrease project efficiency regardless of technology advancements.

Change management shows that organizations need to provide training and establish open communication channels and involve stakeholders to achieve efficiency gains from their new technological implementations (Turner, 1999). Project teams will not achieve their expected efficiency improvements because they will either use digital tools

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

incorrectly or fail to convert predictive data into operational decisions when they do not receive proper training.

Digital Twin–Enabled Predictive Maintenance

The implementation of Digital Twin predictive maintenance combines two advancing research areas which involve creating detailed virtual models of physical systems and using data analytics to predict equipment failures and schedule maintenance operations. The research review combines the most reliable studies which focus on four main subjects about Digital Twins for maintenance operations. The review organizes its findings into four sections which examine (1) Digital Twin maintenance definitions together with its architectural elements (2) predictive analytics methods for remaining useful life estimation (3) research studies which prove Digital Twin-based predictive maintenance works in real-world settings and (4) researchers need to address Digital Twin deployment obstacles and establish governance structures and identify remaining research areas. The document establishes connections between operational systems and actual results which users can apply to their facility and asset management activities.

Architectural Components of the Digital Twin for Maintenance

The academic community defines Digital Twins as dynamic digital models which duplicate physical systems through ongoing data communication and model refresh processes. Boschert and Rosen (2016) defined the simulation dimension of the Digital Twin which functions as a virtual space that enables users to simulate physical system behavior for testing and validation purposes. Kritzinger and his colleagues (2018) established a classification system which divides digital models into three categories of digital shadows and fully realized Digital Twins. The authors established that Digital Twins require systems to maintain real-time bidirectional synchronization for achieving true Digital Twin status.

Digital Twin systems which provide maintenance robustness consist of four connected elements which start with sensor and data acquisition followed by data integration and storage then analytical and prognostic models and finally decision support and visualization. Tao Zhang Liu and Nee (2018) described an industrial Digital Twin framework which unites sensor information with physical models and analytical tools to provide immediate operational insights and operational choices. The research by Van Dinter Slot and Körtner (2022) combined different predictive maintenance architectures to show that Digital Twin effectiveness results from uniting physical simulation with data-based learning methods.

Digital Twin systems for maintenance need hybrid approaches because they need simulation models with high accuracy to model equipment deterioration and machine learning models that can identify operational failure patterns from real-time data.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Predictive Analytics, Prognostics, and Remaining Useful Life Estimation

The success of predictive maintenance depends on both effective anomaly detection and precise remaining useful life prediction (Liu et al., 2025) ;(Repetto, 2025) published a significant review which examined statistical and data-based methods for remaining useful life prediction through their identification of survival model categories and state-space models and nonparametric machine learning approaches. The taxonomy serves as a valuable resource which helps users pick appropriate prognostic methods for Digital Twin implementation (Dihan et al., 2024).

The development of machine learning methods for predictive maintenance has reached an advanced stage. Susto and his colleagues (Susto et al., 2015) showed that industrial detection accuracy improves through ensemble and multiple-classifier systems which unite different model capabilities. Research following this work developed Digital Twin frameworks which combine predicted component health states with simulation scenarios to predict how operational loads will impact future degradation patterns. (Zhong, et al 2023) demonstrate that using multiple prognostic methods within Digital Twin systems enables the creation of reliable remaining useful life predictions through output combination.

Research studies demonstrate that hybrid prognostic systems which unite physical degradation models with data-based improvement methods deliver maximum value to users. You and Yuan and their colleagues (2022) analyzed Digital Twin progress for predictive maintenance through their study which demonstrated that hybrid models outperform black-box methods because they provide better generalization and interpretability. The system uses physics-based explanations through machine learning to detect operational data patterns which cannot be explained by current models.

Empirical Applications and Case Studies

Multiple research studies demonstrate through empirical evidence how Digital Twin technology supports predictive maintenance operations in actual industrial environments. The research by Luo et al. (2020) presented a predictive maintenance system which combined Digital Twin technology with condition monitoring and machine learning for numerical control machine tools to achieve better fault identification and shorter production interruptions than standard maintenance practices. The implementation of prognostic models inside Digital Twins through industrial case studies proves their ability to enhance intervention scheduling precision. Digital Twin-based predictive maintenance through systematic literature reviews shows increasing interest in practical applications of this technology. Van Dinter et al. (2022) performed a systematic review which revealed that sensor data quality and modular modeling and stakeholder participation emerged as key elements for success. Zhong and his colleagues (2023)

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

published an open-access survey which studied design decisions and system deployment methods for Digital Twin predictive maintenance systems to show their effectiveness in manufacturing and heavy equipment operations (Khan et al., 2025).

The research indicates that these methods have been used for monitoring both building operations and infrastructure systems. Digital Twin models have been used by researchers to monitor heating ventilation and air conditioning systems and elevators and building structures through continuous data collection which helps identify system failures and schedule maintenance before building outages occur. The research findings from these applied studies demonstrate that Digital Twin prognostic systems help organizations reduce their unplanned maintenance requirements while simultaneously enhancing their equipment operational readiness.

Implementation Challenges, Data Governance, and Research Gaps

The implementation of this approach faces significant obstacles which prevent its widespread adoption. The main issues in this situation involve data quality and interoperability problems. The research of (Renard, et 2024) shows that sensor diversity and different data structure systems prevent the development of accurate Digital Twins. The research by Van Dinter, et al. (2022) demonstrated that learned prognostic models face two major operational barriers which stem from insufficient historical failure documentation and insufficient event identification information.

Model explainability and trust are also critical. Deep learning methods generate precise failure predictions but their unexplained operation makes it difficult for maintenance personnel to understand the diagnostic information they need. The authors of (You et al. (2022) and (Zhong et al. (2023) suggest two methods to enhance stakeholder trust through explainability techniques and by uniting physical models with data-based components.

The Digital Twin faces two main challenges which stem from its need to scale up and maintain its operational state throughout its entire lifecycle. Digital Twins need continuous updates because equipment replacements and sensor configuration changes and operating regime modifications occur. The research by Luo et al.(2020) demonstrated that physical asset digital replica synchronization requires additional operational work which reduces expected operational efficiency when not properly controlled. The research identifies three essential areas which need attention because Digital Twins collect important operational information which requires protection through strong policies and secure system designs (Repetto, 2025).

The current research lacks essential information according to multiple studies. The research field lacks studies which measure investment returns through time-based assessments that span from project initiation to operational completion. The current

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

absence of standardized performance metrics for Digital Twin-based predictive maintenance creates obstacles when researchers want to evaluate their results against each other (Abd Wahab et al., 2024). The research requires additional studies about human involvement in Digital Twin systems which define staff interactions with system recommendations and determine necessary changes to operational procedures for achieving projected benefits.

Smart Building Facility Management

Smart building facility management involves a complete set of strategies and systems which use advanced sensing technology and information systems and operational integration to preserve building performance and safety and occupant comfort and extended facility life (Ghansah, 2024). The research about these subject spans multiple fields because it combines building science with information technology and control engineering and management science. The review structures previous studies into six distinct categories which include (1) smart building facility management definitions and boundaries and (2) core enabling technologies and (3) smart building applications and their performance results and (4) building lifecycle integration with asset information models and (5) organizational aspects of governance and workforce management and (6) barriers to implementation and needed research for the future.

METHODOLOGY

The Digital Twin (DT) system development for smart building project management efficiency through predictive maintenance in smart buildings followed a complete methodological framework. The system followed a process which aimed to match the digital ecosystem with actual facility management operations. The first phase required a complete evaluation of building maintenance requirements and project coordination needs through established DT conceptual frameworks. The assessment helped to determine which building assets needed immediate attention and which maintenance parameters required ongoing tracking and which system functions were vital and which performance metrics would show the success of the DT system. The system architecture followed the requirements analysis to create a structure which enabled all sensing devices and building components and communication channels to work together without interruptions. The chosen communication protocols provided reliable data transfer for structural health information along with operational statistics and equipment operating records. The system design included a unified communication system which enabled sensors and actuators to stay connected to supervisory control platforms through stable network links. The project established a strong data collection system which used modern platforms to process and store data while providing real-time visualization capabilities.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

The first step for building the DT required us to determine what operations the system would perform. The main objective involved creating predictive maintenance capabilities to enhance equipment reliability and enable project management teams to make better decisions through equipment performance monitoring and upcoming maintenance needs assessment. The system operated to perform ongoing data acquisition while using machine learning methods for predictive analysis and it maintained automated systems which performed maintenance scheduling and operational adjustments.

The system used distributed sensing devices to monitor equipment vibration and temperature and electrical load and environmental conditions and operational status in real-time. The system used smart meters and energy measurement devices to track both real-time power usage and overall power consumption levels while dedicated sensors monitored equipment deterioration and building condition and outside conditions which impact equipment operation. The system included sensors which tracked thermal conditions and lighting levels and monitored both room occupancy and space utilization. The system used motion sensors together with camera-based monitoring which employed computer vision algorithms for occupancy detection. The system incorporated automated dampers and ventilation systems and mechanical adjusters which function as actuators to execute maintenance operations based on specific events.

The system required a specific communication framework to achieve its interoperability functionality. The system used Message Queuing Telemetry Transport (MQTT) and Hypertext Transfer Protocol (HTTP) for data transmission between sensors and devices and Modbus for energy measurement device communication. The data network operated through wireless and wired connections which used wireless networks to support environmental sensors and wired networks to support mission-critical power meters. The system used a central message broker to handle the reliable transfer and synchronization and routing of real-time data streams.

The dedicated data infrastructure stored all collected data which it could use for both short-term queries and extended storage needs. The system used PostgreSQL to handle its structured data while it stored time-series information in InfluxDB databases. The system used SQLite as its lightweight database to perform localized caching operations at sensor and gateway locations. The system operated from a Linux-based server which contained multi-core processors together with high-capacity memory and graphics processing hardware for executing artificial intelligence functions. The system-maintained operation through backup power supplies which protected against power outages. The deployment of the data acquisition system led to the establishment of predictive models which would forecast when assets needed maintenance (Benhanifia et al., 2025). The system used machine learning algorithms to analyze past performance information for predicting maintenance requirements and identifying system

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

irregularities and predicting equipment deterioration patterns. The development of machine learning pipelines used open-source platforms which included TensorFlow and Scikit-Learn and KNIME. The models received updates through real-time feedback systems which operated to preserve their accuracy when operational environments shifted (da Costa et al., 2024). The system implemented automation systems to enhance maintenance planning optimization and project coordination operations. The system used predictive insights together with automated control logic to perform scheduled interventions and operational setting adjustments and maintenance priority recommendations which avoided equipment breakdowns that could stop project work (Molęda et al., 2023). The system used edge computing to perform urgent analytics at the edge which reduced the time needed to make decisions.

The system included a complete visualization platform which enabled users to monitor their systems and create strategic plans. The system displayed interactive dashboards which showed essential performance indicators that included equipment health scores and predicted failure times and maintenance records and project effect measurements (Zhao et al., 2022). The system used Power BI to combine data into user-friendly visualizations and Node-RED for workflow management and system integration tasks. The system included a three-dimensional visualization module which enabled facility managers to view a building model in virtual space for real-time assessment of asset performance.

The DT required extensive validation tests which proved its operational precision and dependability and fast reaction times before it could be used on a broad scale. The evaluation of machine learning performance involved the comparison of real-world sensor data with model-generated predictions (Zhao et al., 2022). The system stability underwent assessment through stress-testing procedures which operated under different operational conditions. The control system received improvements which made it more sensitive while minimizing the number of unneeded system activations.

The method produced a Digital Twin with high fidelity which enables predictive maintenance operations and enhances project management operational performance. Real-time data analysis together with intelligent prediction systems and automated control systems create a system which improves both the flexibility and expansion capabilities of facility management operations (Shen et al., 2020). The combination of advanced visualization tools and secure data infrastructure enables improved decision-making, better resource allocation, and more effective maintenance planning.

Functional Requirements

The Digital Twin model requires these five functions to achieve successful implementation for smart building predictive maintenance operations.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Predictive Maintenance and Asset Performance Forecasting

The system tracks how much power different major building systems use while it predicts their future energy usage.

The system monitors both real-time and total energy consumption of essential machinery systems.

The system tracks both operational status and runtime performance of mechanical actuators.

The research measures total electricity usage which includes lighting systems and utility services and climate control systems.

Environmental and Structural Condition Monitoring

The process involves tracking environmental elements which impact equipment operational performance.

The system tracks multiple environmental factors which include temperature and humidity levels and particulate matter concentrations and air quality and carbon dioxide gas levels.

Evaluating thermal comfort metrics and lighting adequacy

The system tracks both window positions and mechanical system operating states.

Occupancy and Space Utilization Analysis

The system uses motion sensors to detect when people enter the space in real-time.

The process of using computer vision methods to determine how many animals exist in their environment.

The system connects building occupancy data to equipment operational patterns and scheduled maintenance requirements.

Interoperability Requirements

The system needs to support various communication protocols for operation.

The system supports wireless and wired communication standards.

The system enables users to establish protected links between their network and outside systems.

Data Management

The system maintains performance data through extended storage and proper organizational systems.

The system enables users to perform data queries and retrieve information while maintaining real-time data synchronization.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Data Visualization

The system uses dashboards to show data which users can access through these platforms.

The process of adding data to three-dimensional building models.

The functional requirements establish specific measurable elements which enable the Digital Twin to perform predictive maintenance and optimize project management operations

System Requirements

The system needs to fulfill these requirements to achieve operational reliability.

Communication Protocols

The system employs MQTT to monitor environmental and operational sensors.

The system depends on HTTP to distribute environmental data and video analytics information.

The Modbus system functions as an energy monitoring device communication protocol.

The system allows optional implementation of OPC Unified Architecture for achieving standardized interoperability between different systems.

Communication Networks

Wireless networks for sensors and actuators

The power meters and essential controllers of the system operate through wired local network connections.

Data Aggregation Services

The system employs an MQTT broker which enables real-time coordination between all system components.

The power monitoring system employs Schneider Electric EcoStruxure for its operations.

Data Processing Platforms

Node-RED serves as a tool for workflow automation.

The development process includes creating Python and JavaScript machine learning solutions which match specific requirements.

The system will integrate Power BI for visual analytics.

The system enables users to access a three-dimensional modeling interface which provides them with advanced visualization capabilities.

Database Systems

PostgreSQL for structured datasets

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

The system uses InfluxDB to handle time-series data.
SQLite for local data caching

Server Infrastructure

Linux-based server
Multi-core processor (minimum 8 cores and 16 threads)
The system requires at least 1 terabyte of storage.
The system requires a graphics processing unit which must have 12 gigabytes or more of memory.
The system requires at least 64 gigabytes of system memory for operation.
The backup power supply maintains continuous operation of the system.

Machine Learning Ecosystem

The process of model development employs both free open-source solutions and paid commercial software tools.
The organization provides its employees with dedicated analytics platforms which include KNIME.
The system operates with industry-grade sensors which have proven their accuracy in measurement operations.

Security and Access Control

The system enables multiple users to access the system through various permission-based access levels.
The security framework follows international security standards which it uses.

Key Performance Indicators

The Digital Twin–enabled predictive maintenance framework requires Key Performance Indicators (KPIs) to assess its ability to boost project management efficiency in smart building facility management operations. The KPIs track system performance through four different dimensions which include operational and predictive and managerial and integration aspects.

1. Predictive Maintenance Accuracy and Responsiveness

The system achieves 100% accuracy in detecting faults for all four system categories which include HVAC and lighting and surveillance and environmental systems.
The system generates critical asset RUL prediction error measurements which show hours and days.
The analysis presents two key performance indicators which compare anomaly detection times to standard maintenance response periods.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Reduction in unplanned equipment downtime (%).

Energy Consumption Monitoring & Forecasting

The system provides real-time tracking of electrical and thermal and mechanical energy usage which shows both room-level and equipment-level data in watts and kilowatt-hours (W, kWh).

The system evaluates prediction horizon performance through MAE and RMSE metrics for energy demand forecasting models.

The system achieves energy savings through its predictive maintenance scheduling system and automated operational adjustments.

Indoor Environmental Quality (IEQ) Prediction

The system tracks indoor air quality (IAQ) by monitoring CO_2 levels and VOCs and humidity and particulate matter concentrations.

The PMV and PPD thermal comfort prediction indices show their connection to building occupancy patterns and equipment operation status.

The graph shows how the system deviated from its optimal comfort range both before and after it received predictive input.

Occupancy Monitoring and Utilization Forecasting

The system achieves people/time occupancy detection precision through its combination of IoT sensors and ML algorithms.

The system will predict how space will be used to help maintenance teams create schedules which avoid interrupting normal building activities.

The system should optimize its asset scheduling through predictions about when facilities will reach their maximum occupancy levels.

Predictive Control of Building Components

The system needs to develop algorithms which will automatically operate HVAC systems and ventilation and lighting and window and door mechanisms to reach the following goals:

thermal comfort optimization

air quality stabilization

noise reduction

The system tracks operational efficiency improvements by counting the number of times staff members need to perform manual tasks.

The control algorithm demonstrates its performance through two essential metrics which include response time and adjustment precision.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Project Management Efficiency Metrics

The percentage of maintenance-related project delays which decreased after implementing Digital Twin simulation technology.

The system demonstrates enhanced resource allocation efficiency through:

technician dispatch optimization maintenance task prioritization accuracy

The percentage of cost savings which predictive maintenance provides when compared to scheduled or reactive maintenance approaches.

The system reduces administrative work through automated processes and digital workflow management.

Real-Time Visualization and Decision Support

The system uses 3D Digital Twin visualization to monitor systems in real-time while detecting faults and controlling workflow operations.

User response efficiency time required for project managers to assess a fault and initiate corrective actions.

The system requires dashboard functionality which provides users with easy access to monitor multiple parameters while maintaining both system accuracy and user interface usability.

Long-Term Data Management

The system needs to maintain operational and maintenance data storage capabilities which will enable it to handle information management for a minimum period of three years.

Ensuring: data integrity, time-series consistency,

The research focuses on how data structures should match the requirements of Digital Twin systems.

Cybersecurity and Multi-User Access Control

The system uses a data security index which depends on three security layers that include access control and encryption and authentication mechanisms.

System resilience score against unauthorized access attempts.

The Digital Twin cloud services need to follow standard protocols which include OAuth and JWT and TLS for compliance purposes.

Platform Interoperability & Standardization

The system operates at interoperability levels through its implementation of standardized communication protocols which include MQTT and HTTP and REST API and BACnet and Modbus and ONVIF.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

The system achieved what percentage of successful integrations when it added new devices and data streams.

The system demonstrates its ability to perform cross-platform communication through its evaluation of latency and throughput performance.

Validation Matrix (Re-Engineered Version)

The validation matrix links system requirements to Digital Twin capabilities and machine learning results and performance indicators which measure project management efficiency enhancement.

Table 1:

Requirement Level	System Requirement	Digital Twin Functionality	Associated KPI(s)	Validation Method
Operational	Real-time energy and IEQ monitoring	Continuous sensor data acquisition + 3D environment mapping	Energy forecast accuracy, CO_2/PMV prediction performance	Time-series evaluation, RMSE/MAE
Predictive	Early anomaly detection for equipment	ML-based fault detection + RUL estimation models	Fault detection accuracy, reduction in downtime	Confusion matrix, RUL error metrics
Optimization	Automated building control and scheduling	Digital Twin control algorithms + occupancy prediction	Comfort indices stability, space utilization efficiency	A/B testing, algorithm response-time analysis
Management	Improved planning of maintenance workflows	Simulation of maintenance scenarios and resource allocation	Project delay reduction, cost savings	Pre- vs post-implementation comparison
Visualization	Real-time 3D monitoring and dashboards	Multi-layer Digital Twin visualization	User response time, dashboard usability	User studies, performance logging
Interoperability	Integration with diverse IoT devices	MQTT, API, HTTP, ONVIF, BACnet interfaces	Communication latency, integration success rate	Stress tests, packet/latency analysis
Security	Protect building and maintenance data	Multi-user authentication + encryption	Security compliance index	Penetration testing, audit logs
Data Management	Long-term historical data storage	Cloud-based time-series and structured DB	Data retention reliability, integrity score	Data integrity checks, storage benchmarks

Communication Protocols

The system operates through standardized IoT protocols which handle communication between system devices and the edge server. HTTP enables broad compatibility and

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

stable data exchange between registered devices which supports a reliable Digital Twin (DT) infrastructure. MQTT enables IoT networks to use lightweight event-driven messaging through its requirement of a specific broker service for its implementation. The system should use HTTP whenever possible because it helps reduce the need for extra server operations.

The industrial data exchange between energy meters uses Modbus but ONVIF serves for fast video stream retrieval from IP cameras. REST APIs enable HTTP-based management of structured data requests which allows users to control data traffic and set update rates and maintain system stability.

The system design process included standardization of protocol selection to achieve system interoperability. The Shelly units along with their built-in web servers enable HTTP communication between devices which operates without requiring MQTT brokers for operation. The Schneider energy meters use Modbus over Ethernet for connection while the weather station retrieves data through REST APIs and the cameras function on ONVIF. The system assigns static IP addresses to all devices which maintain network accessibility throughout system restarts.

The power monitoring system from Schneider operates through its EcoStruxure managed wireless protocol. The Mosquitto broker operates as the chosen MQTT messaging service for third-party devices which need this protocol.

Data Platform

The project required open-source platforms which offered experimental functionality and complete customization options. The final selection of tools emerged from evaluating multiple available choices.

Node-RED operates as an open-source workflow-based platform which runs on Node.js to enable IoT protocol support and event management and custom logic programming and fast development capabilities.

Home Assistant, OpenHAB, and OpenRemote received evaluation as potential alternatives but Node-RED became the selection because it offers flexible operation together with broad library resources and reliable performance and extensive community backing.

The Node-RED system operated from a Debian-based virtual machine. The system features a visual programming interface which allows users to connect IoT devices and Python scripts and KNIME tools for complex data analysis.

The storage system contains two separate data storage sections which include long-term storage and fast data retrieval systems.

PostgreSQL functions as a database system which provides persistent structured data storage.

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

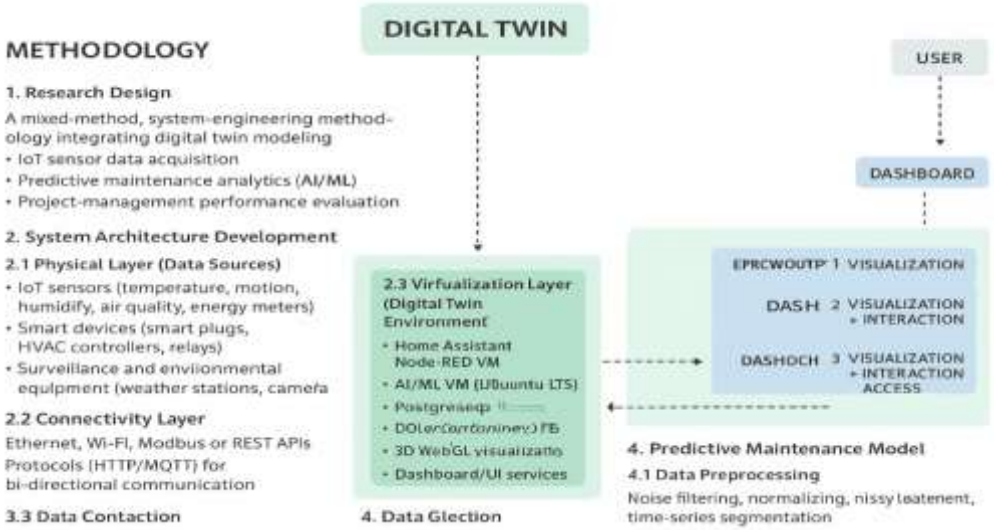
SQLite serves as a lightweight caching solution for short-term data storage.

Time-series data requires Influx DB as an essential component for predictive and machine learning workflows.

The team chose Power BI for their data analytics and visualization needs and implemented VCAD 3.0 to connect BIM models directly to dashboards which allowed users to interact with spatial and sensor data in real time. The system follows ISO 27000 principles to manage user access through secure role-based authorization.

Software Architecture

The system uses the software architecture described in this section which explains both communication protocols and data management platform and its supporting services. The complete system design appears in Figure 1 which shows the system layout.



Case Study

The project aims to create a Digital Twin prototype which will be applied to specific office areas located in a historic institutional building. The research aims to evaluate how real-time monitoring systems and predictive maintenance approaches function for smart building operations. The system focuses on four main areas which include energy efficiency and indoor environmental quality and component-level predictive maintenance and space utilization.

The research team chose three rooms for study because they serve important functions and present difficulties regarding their energy consumption and environmental conditions and user activities.

The system focuses on four core areas which form its main structure.

Energy monitoring and optimization.
Indoor air quality assessment.
Predictive maintenance of building components. Workplace utilization and management

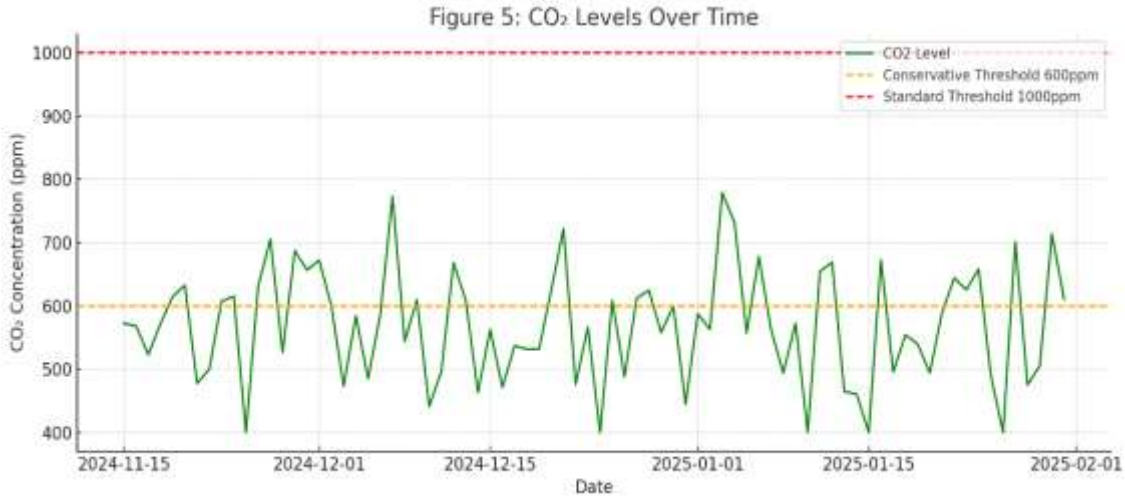
RESULTS

Air Quality Forecasting

The evaluation of indoor air quality used CO_2 concentration measurements to determine room occupancy levels through a method based on data analysis. The research method required researchers to establish CO_2 threshold values and to prepare sensor information and execute all required mathematical operations. The research team performed their analyses within environments that maintained controlled temperature and humidity levels to reduce external factors which could affect their results.

The measurement of CO_2 levels in indoor spaces serves as a vital air quality metric because high concentrations create adverse effects on human health and comfort and reduce mental performance. The research used 600 ppm as its safety threshold instead of the typical 1000 ppm standard. The sensor placement followed UNI EN ISO 16000 guidelines to achieve precise measurement results.

The measured CO_2 concentrations appear in Figure 5 which shows data from 15 November 2024 through 31 January 2025. The multi-colour line chart enables users to distinguish between normal air quality levels below 600 ppm and critical levels above 600 ppm which helps them identify when air quality becomes worse.



The air quality becomes unacceptable when carbon dioxide levels surpass 600 ppm.
The peaks in the graph indicate when the space experienced longer periods of occupancy and inadequate air movement.

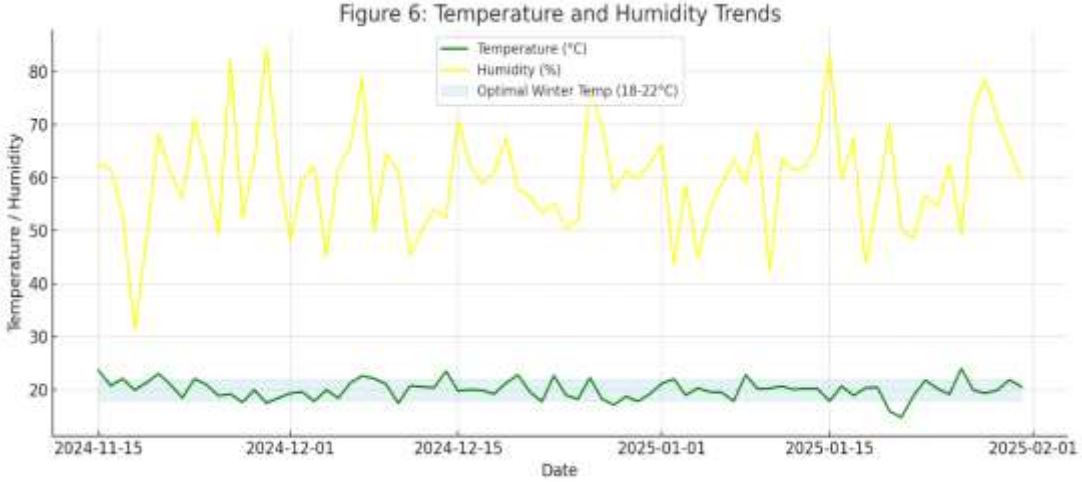
The maintenance of CO_2 levels at or below the established threshold helps protect both human health and create comfortable living spaces.

The suggested figure should display CO_2 levels through a line chart which uses green for safe zones and orange for moderate zones and red for critical zones.

Thermal Comfort

The indoor environment requires both optimal temperature and humidity levels to support human health and comfort. The monitoring of these parameters becomes essential for buildings which lack Building Management System (BMS) because their HVAC system transitions at irregular intervals. The analysis required the system to operate between 18–22 °C in winter and 23–26 °C in summer while maintaining relative humidity between 50–80%. The established ranges follow the Perceived Mean Vote (PMV) model framework. The graph in Figure 6 demonstrates temperature (green) and humidity (yellow) patterns which span from 15 November 2024 to 31 January 2025 to identify the best winter temperature range.

Figure 6: Temperature and Humidity Trends

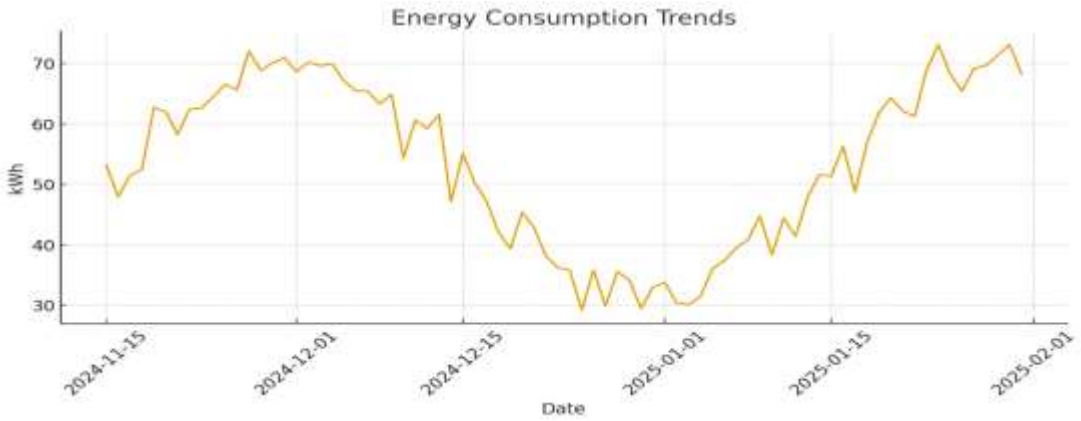


The data shows when operational conditions moved outside their recommended optimal zones. The system allows for ongoing surveillance which helps organizations achieve better control of their HVAC energy consumption. The established temperature ranges help both people in the building to feel comfortable and prevent the spread of infectious agents.

Power Consumption

A Long Short-Term Memory (LSTM) network was developed to forecast energy consumption based on temperature and humidity data. The model detects time-based patterns which helps organizations create strategic energy plans and discover potential energy conservation methods. The graph in Figure 7 shows energy usage patterns (kWh)

throughout the period from 15 December 2024 until 31 January 2025. The measured cyclic pattern shows the pattern of office usage and daily workplace activities. Analysis: The system shows its highest energy consumption during times when the building contains the most people. The analysis of environmental factors which affect energy usage helps organizations optimize their operational activities.



Data Preparation and Model Training

The first step of data preparation involved. The process includes two stages which involve dataset loading and cleaning and missing value interpolation. The process of uniting data points into time segments which span one hour each. The system performs normalization on power consumption data to create values which range from 0 to 1. The process of creating sequential data for LSTM input requires a sliding window approach. The LSTM model detected both short-term and long-term patterns in the data through its implementation of dropout layers which helped prevent overfitting. The results from training and validation appear in Figure 8.

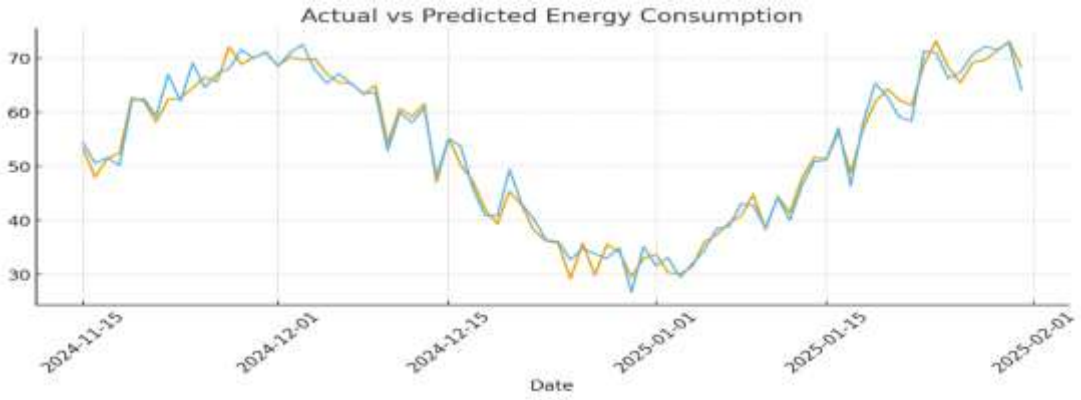


Figure 8: The convergence curve shows that the training process remains stable while the loss values remain at a minimum. The model achieved high predictive accuracy because its RMSE value reached 0.04.

DISCUSSION

The current study emphasizes the value of design optimization, digital tools, and frameworks for the improvement of project management in various fields. In the literature and case studies analyzed, project success was affected by the degree of complexity, costs, schedule uncertainties, people, and the regulatory environment. More specifically, predictive analytics, machine learning, and digital twin frameworks, which are evidence-based tools, are useful for visibility, forecasting, and decision-making.

Another critical issue is the time and cost involved, which are recurring problems in industrial and infrastructure projects. The studies reviewed indicate that a lack of planning, poor stakeholder coordination, lack of monitoring, and change management are the main reasons for delays. These studies corroborate previous studies, which indicate that there are no poor project execution outcomes, which are sensitive to planning, availability of materials, capacity of contractors, and financing. In addition, the use of digital project delivery including BIM, IoT monitoring, and simulators. From a managerial perspective, the discussion highlights the importance of organizational maturity in adopting modern project methodologies. Successful implementations typically involve strong leadership support, capacity building, effective communication systems, and structured governance frameworks. The reviewed cases also indicate that sustainable project outcomes require balancing performance goals with environmental, social, and financial considerations. This aligns with global trends emphasizing green project delivery, smart monitoring, and lifecycle optimization.

Overall, the study contributes new insights by integrating multiple disciplines—digital transformation, risk management, simulation modelling, and strategic planning—into a unified approach for optimizing project success. This multidisciplinary view reflects the current evolution of project management practice toward more intelligent, automated, and data-centric ecosystems.

CONCLUSION

This study concludes that optimizing project management requires a combination of advanced digital technologies, data-driven strategies, and robust managerial frameworks. Evidence from the reviewed materials confirms that conventional project management approaches are insufficient for dealing with modern complexity, especially in infrastructure, industrial, and smart system environments. Tools such as predictive analytics, simulation engines, BIM, IoT, and digital twins have demonstrated measurable advantages in minimizing delays, reducing cost overruns, improving coordination, and enhancing decision accuracy.

Furthermore, the study affirms that integrating technological innovation with human expertise, institutional support, and strategic communication yields more sustainable and

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

resilient project outcomes. By addressing contextual challenges and leveraging modern computational capabilities, organizations can significantly enhance performance, meet stakeholder expectations, and achieve long-term value creation.

RECOMMENDATIONS

Based on study findings, the following recommendations are proposed:

1. Adopt Advanced Digital Systems: Organizations should integrate BIM, IoT sensors, digital twins, and predictive analytics to improve real-time monitoring, forecasting accuracy, and decision support.
2. Strengthen Early-Stage Planning: Proper feasibility studies, risk assessments, and cost time simulations should be conducted before project execution to minimize uncertainties.
3. Enhance Communication & Collaboration: Establishing structured communication frameworks among contractors, consultants, suppliers, and clients will reduce coordination gaps and delays.
4. Improve Risk Management Practices: Project environments should implement proactive risk identification, quantitative risk modelling, and continuous monitoring systems.
5. Invest in Human Capacity Development: Training programs on digital tools, data literacy, simulation methods, and modern PM methodologies (Agile, Lean, Stage-Gate) are essential for success.
6. Establish Governance & Policy Support: Standardized reporting frameworks, contractual guidelines, and compliance mechanisms can help reduce ambiguity and escalate accountability.
7. Promote Sustainable Project Delivery: Project decisions should integrate environmental, financial, and social sustainability metrics to align with global development goals.

REFERENCES

Abd Wahab, N. H., Hasikin, K., Wee Lai, K., Xia, K., Bei, L., Huang, K., & Wu, X. (2024). Systematic review of predictive maintenance and digital twin technologies: Challenges, opportunities, and best practices. PeerJ Computer Science, 10, e1943. https://doi.org/10.7717/peerj-cs.1943

Al-Fuqaha, A., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of Things: A survey on enabling technologies, protocols, and applications. *IEEE Communications Surveys & Tutorials, 17*(4), 2347–2376. https://doi.org/10.1109/COMST.2015.2444095

Alves, M., Carreira, P., & Costa, A. A. (2017). BIMSL: A generic approach to the integration of building information models with real-time sensor data. *Automation in Construction, 84*, 304–314. https://doi.org/10.1016/j.autcon.2017.09.012

Attaran, M., & Celik, B. G. (2023). Digital twin: Benefits, use cases, challenges, and opportunities. *Digital Atlas Journal*, 100165. https://doi.org/10.1016/j.dajour.2023.100165

Azhar, S. (2011). Building information modeling: Trends, benefits, risks, and challenges for the architecture, engineering, and construction industry. *Leadership and Management in Engineering, 11*(3), 241–252. https://doi.org/10.1061/(ASCE)LM.1943-5630.0000127

Braun, T., Wetzstein, S., & Seiger, R. (2022). Leveraging Digital Twin data for strategic building maintenance planning. *Automation in Construction, 138*, 104226.

Ighofiomoni, M. O., Badrudeen, Y. A., Ojenike, A. O., Samson, O. E., Abioye, S. O., Chinonyerem, C. A., & Sofowoke, O. O. (2025). Federated machine learning-based cybersecurity framework for autonomous and connected vehicles: Privacy-preserving real-time intrusion detection and adaptive threat mitigation in V2X communications. *International Journal of Applied and Advanced Engineering Research, 10*(5). https://doi.org/10.70382/mejaaer.v10i5.044

Carvalho, D., Soares, N., Vita, R., & del Real Torres, A. (2021). Predictive maintenance of heating, ventilation, and air conditioning systems using machine learning. *Energy and Buildings, 241*, 110944.

Chatsuwan, M. (2025). Enhancing facility management with a building information model and Internet of Things integration for indoor environmental quality monitoring. *Buildings, 15*(11), 1928. https://doi.org/10.3390/buildings15111928

Chatzikonstantinidis, K. (2025). Energy management of smart buildings during crises and extreme events: Lessons from the COVID-19 pandemic and beyond. *Energy Research & Social Science, 91*, 102786. https://doi.org/10.1016/j.erss.2025.102786

Dihan, M. S., Akash, A. I., Tasneem, Z., Das, P., Das, S. K., Islam, M. R., Islam, M. M., Badal, F. R., Ali, M. F., Ahamed, M. H., Abhi, S. H., Sarker, S. K., & Hasan, M. M. (2024). Digital twin: Data exploration, architecture, implementation and future. Heliyon, 10(e26503). https://doi.org/10.1016/j.heliyon.2024.e26503

Ding, L., Zhou, Y., & Akinci, B. (2021). Digital Twin–based structural health monitoring: Current trends and future directions. *Engineering Structures, 234*, 111977. https://doi.org/10.1016/j.engstruct.2021.111977

Gbahabo, P. T., & Ajuwon, O. (2017). *Effects of infrastructure project cost overruns and schedule delays in Sub-Saharan Africa*. Paper presented at the 11th International Conference on Social Sciences.

Ghansah, F. A. (2024). Digital twins for smart building at the facility management stage: A systematic review of enablers, applications, and challenges. Smart and Sustainable Built Environment, 14(4). https://doi.org/10.1108/SASBE-10-2023-0298

Hodavand, F., Ramaji, I., Sadeghi, N., & Zandi Goharrizi, S. (2025). *Digital twin-enabled framework for intelligent monitoring and anomaly detection in multi-zone building systems*. Buildings, 15(22), 4030. https://doi.org/10.3390/buildings15224030

Hodavand, F., Ramaji, I., Sadeghi, N., & Zandi Goharrizi, S. (2025). Digital twin-enabled framework for intelligent monitoring and anomaly detection in multi-zone building systems. Buildings, 15(22), 4030. https://doi.org/10.3390/buildings15224030

Iliuță, M.-E., Moisescu, M.-A., Pop, E., Ionita, A.-D., Caramihai, S.-I., & Mitulescu, T.-C. (2024). Digital Twin A review of the evolution from concept to technology and its analytical perspectives on applications in various fields. Applied Sciences, 14(13), 5454. https://doi.org/10.3390/app14135454

oIranshahi, K., Brun, J., Arnold, T., Sergi, T., & Müller, U. C. (2025). Digital twins: Recent advances and future directions in engineering fields. Intelligent Systems with Applications, 26, 200516. https://doi.org/10.1016/j.iswa.2025.200516

Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology, 29*, 36–52. https://doi.org/10.1016/j.cirpj.2020.02.002

Khajavi, S. H., Motlagh, N. H., Jaribion, A., & Holmström, J. (2019). Digital Twin: Vision, opportunities, and challenges. *IEEE Access, 7*, 149783–149801. https://doi.org/10.1109/ACCESS.2019.2946515

Liu, Y., Wen, J., & Wang, G. (2025). A comprehensive overview of remaining useful life prediction: From traditional literature review to scientometric analysis. Machine Learning with Applications, 18, 100704. https://doi.org/10.1016/j.mlwa.2025.100704

Lu, Q., Parlikad, A. K., & Woodall, P. (2020). Developing a Digital Twin at building and city levels: Case study of West Cambridge campus. *Automation in Construction, 118*, 103278. https://doi.org/10.1016/j.autcon.2020.103278

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Machacek, Z., Hercik, R., Vaclavik, A., & others. (2025). Modern trends and industrial use cases of digital twin technology with 3D behavioral representation. Journal of Intelligent Manufacturing. https://doi.org/10.1007/s10845-025-02709-y

Ogunnowo, E. O., Adewoyin, M. A., Fiemotongha, J. E., Igunma, T. O., & Adeleke, A. K. (2024). A conceptual framework for digital twin deployment in real-time monitoring of mechanical systems. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 2350–2367. https://doi.org/10.62225/2583049X.2024.4.6.4353

Opoku, A., Perera, S., Osei-Kyei, R., Rashidi, A., & Arashpour, M. (2021). Digital Twin application in facilities management: A critical review. *Journal of Facilities Management, 19*(5), 544–569. https://doi.org/10.1108/JFM-02-2021-0025

Osei-Owusu, J., Bahadori-Jahromi, A., Amirkhani, S., & Godfrey, P. (2025). *Automating building energy performance simulation with EnergyPlus using modular JSON–Python workflows: A case study of the Hilton Watford Hotel*. **Sustainability, 17**(22), 10317. https://doi.org/10.3390/su172210317

Osei-Owusu, J., Bahadori-Jahromi, A., Amirkhani, S., & Godfrey, P. (2025). Automating building energy performance simulation with EnergyPlus using modular JSON–Python workflows: A case study of the Hilton Watford Hotel. Sustainability, 17(22), 10317. https://doi.org/10.3390/su172210317

Pan, Y., & Zhang, L. (2021). A BIM-digital twin framework for sustainable building performance management. *Journal of Cleaner Production, 318*, 128180. https://doi.org/10.1016/j.jclepro.2021.128180

Pašek, J., & Sojková, V. (2018). Facility management of smart buildings. *International Review of Applied Sciences and Engineering, 9*(2), 181–189. https://doi.org/10.1556/1848.2018.9.2.16

Renard, D., Saddem, R., Annebicque, D., & Riera, B. (2024). From sensors to digital twins toward an iterative approach for existing manufacturing systems. Sensors, 24(5), 1434. https://doi.org/10.3390/s24051434

Repetto, M. (2025). Cybersecurity digital twins: Concept, blueprint, and challenges for multi-ownership digital service chains. Journal of Information Security and Applications, 76, 104299. https://doi.org/10.1016/j.jisa.2025.104299

Repetto, M. (2025). Cybersecurity digital twins: Concept, blueprint, and challenges for multi-ownership digital service chains. Journal of Information Security and Applications, 76, 104299. https://doi.org/10.1016/j.jisa.2025.104299

Sepasgozar, S. (2021). Differentiating Digital Twin from Digital Shadow: Implications for future research. *Advanced Engineering Informatics, 48*, 101296. https://doi.org/10.1016/j.aei.2021.101296

Shahzad, M., Shafiq, M. T., Douglas, D., & Kassem, M. (2022). Digital twins in built environments: An investigation of the characteristics, applications, and challenges. Buildings, 12(2), 120. https://doi.org/10.3390/buildings12020120

Shahzad, M., Shafiq, M. T., Douglas, D., & Kassem, M. (2022). Digital twins in built environments: An investigation of the characteristics, applications, and challenges. Buildings, 12(2), 120. https://doi.org/10.3390/buildings12020120

Shen, X., Hao, L., & Xue, H. (2020). Simulation-driven building maintenance scheduling using digital twin models. *Journal of Cleaner Production, 276*, 123197. https://doi.org/10.1016/j.jclepro.2020.123197

Susto, G. A., Schirru, A., Pampuri, S., McLoone, S., & Beghi, A. (2015). Machine learning for predictive maintenance: A multiple classifiers approach. *IEEE Transactions on Industrial Informatics, 11*(3), 812–820. https://doi.org/10.1109/TII.2014.2349359

West, J., Siddhpura, M., Evangelista, A., & Haddad, A. (2024). Improving equipment maintenance Switching from corrective to preventative maintenance strategies. Buildings, 14(11), 3581.: Hamasha, M. M., Bani-Irshid, A. H., Al Mashaqbeh, S., Shwaheen, G., Al Qadri, L., Shbool, M., Muathen, D., Ababneh, M., Harfoush, S., Albedoor, Q., & Al-Bashir, A. (2023). Strategical selection of maintenance type under different conditions. Scientific Reports, 13(1), 15560. https://doi.org/10.1038/s41598-023-42751-5.

Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023). Overview of predictive maintenance based on digital twin technology. Heliyon, 9(12), e14534. https://doi.org/10.1016/j.heliyon.2023.e14534

Zou, Y., Xu, Q., & Wang, R. (2023). Data interoperability challenges in Digital Twin applications for intelligent buildings. *Energy and Buildings, 282*, 112780. https://doi.org/10.1016/j.enbuild.2023.112780

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]

Zou, Y., Xu, Q., & Wang, R. (2023). Data interoperability challenges in Digital Twin applications for intelligent buildings. *Energy and Buildings, 282*, 112780. https://doi.org/10.1016/j.enbuild.2023.112780

Zwikael, O., & Smyrk, J. (2011). *Project management for the creation of organisational value*. Springer. https://doi.org/10.1007/978-1-84996-170-0

EDITOR-IN-CHIEF
Prof. W. F. HILL [MALAWI]