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Integration of Artificial Intelligence and Smart Technologies in Offsite Construction: A Comprehensive Review

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Abstract: Due to the ongoing rapid pace of advancement in information technology, the integration of Artificial Intelligence (AI) and Smart Technologies (ST) in offsite construction is transforming the industry by enhancing efficiency, innovation, and safety. This comprehensive review examines the application of AI and ST subfields, including Machine Learning (ML) algorithms such as k-Nearest Neighbors (k-NN), logistic regression, linear regression, Support Vector Machines (SVM), and neural networks, as well as Deep Learning (DL) algorithms like Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), Variational Autoencoders (VAE), and Recurrent Neural Networks (RNN), in offsite construction. Utilizing secondary data, descriptive survey methods, systematic review, and content analysis, the study maps the current state of AI and ST applications such as Building Information Modeling (BIM) and other technologies such as the Internet of Things (IoT), Augmented Reality (AR), digital twins and identifies trends, opportunities, and challenges. This review also discusses the need for research investment and the development of regulatory frameworks to foster innovation and sustainable growth. Ethical considerations, including data quality, transparency, privacy, employment impacts, and governance, are also critical to the responsible adoption of these technologies. This research concludes with a call for strategic research and development to bridge existing gaps and fully leverage AI and ST for industry-wide benefits. Grounded based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the review provides valuable information to academics, practitioners, and policymakers aiming to harness the benefits of AI and ST in offsite construction.

Keywords: Artificial Intelligence; Smart Technologies; Machine Learning; Robotics; Building Information Modeling

1. INTRODUCTION

Offsite Construction refers to the process of planning, designing, fabricating, transporting, and assembling building elements at a location other than their final site of installation. It marks a significant evolution in the building industry, emphasizing efficiency, waste reduction, and minimized onsite labor. The evolution of Artificial Intelligence (AI) and Smart Technologies (ST) within this domain signifies a sustainable advancement that is expected to redefine productivity, efficiency, and safety standards (Chugh et al., 2024). The fusion of AI and ST in offsite construction not only promises to elevate these parameters but also introduces a new paradigm in tackling traditional and emerging industry challenges.

The emergence of the COVID-19 pandemic has undeniably accelerated the adoption of innovative technologies across various sectors, including construction (Ali Hassony & Ahmed, 2024). Amid the disruption, the pandemic catalyzed a transformative shift, highlighting the indispensable role of digital technologies in ensuring resilience and continuity. AI, with its expansive capabilities ranging from data analysis to predictive modeling, has emerged as a valuable technology, enabling businesses to navigate the complexities of the pandemic-era landscape. This period of intense digital transformation highlighted the multifaceted applications of AI, from optimizing operational efficiency to fostering innovative problem-solving approaches.

Historically, AI's journey began with its ability to perform tasks that were considered exclusively human domains, such as logical reasoning and strategic game-playing (Sanders & Wood, 2024). This marked a departure from the traditional perception of computers as mere calculators, unveiling the potential of AI as a dynamic and versatile tool. Over the years, the impact of AI has been predominantly positive, revolutionizing various aspects of work and life. The construction industry, known for its cautious approach towards digital adoption, has not remained untouched by the AI revolution. The integration of AI and ST in construction processes signifies a leap towards modernization, driven by the need for cost savings, efficiency, and innovative solutions to complex problems. This strategic integration aligns with the broader trends of digitalization, promising to redefine the construction landscape in line with contemporary digital trends.

As multiple researchers agree, AI and ST are integrated in different fields and activities basically because of their huge benefits, which include saving of costs, reduction of labour burdens on humans, solving problems, ushering innovation, and enabling firms to gather, store, and process a large amount of data and knowledge (Taheri et al., 2022). Despite the growing interest in integrating Artificial Intelligence (AI) and Smart Technologies (ST) in offsite construction, there remains a significant gap in the systematic study of these technologies. Previous studies, such as those by (Pan et al., 2022), have highlighted the essential role of AI and robotics in prefabricated construction but noted the lack of comprehensive reviews on this integration. Additionally, while various AI subfields like Machine Learning (ML) and robotics have been explored, there is limited research on the application of ML and Deep Learning (DL) algorithms with their potentiality and smart technologies such as Building Information Modeling (BIM), Internet of Things (IoT) devices, Augmented Reality (AR), digital twins, blockchain technology, drones, and wearable technologies in offsite construction.

Moreover, the integration of AI and ST in offsite construction raises crucial ethical considerations that necessitate responsible and sustainable implementation. These ethical issues include data quality, reliability, and accuracy; transparency and accountability; privacy and data protection; employment and human welfare; and ethical governance and moral responsibility (Abioye et al., 2021; Observer, 2024). Addressing these ethical concerns is essential to building trust among stakeholders and ensuring that the deployment of AI and ST does not lead to unintended negative consequences.

This paper aims to address these gaps by providing a systematic review of the integration of AI and ST in offsite construction. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), this work provides a critical examination of the current state of AI and ST applications in offsite construction (Venkatesh et al., 2003). The study identifies key trends, opportunities, and challenges, offering valuable insights for academics, practitioners, and policymakers by mapping the landscape through a systematic review of existing published research. The findings highlight the use of AI and ST approaches in offsite construction holds the promise of revolutionizing the industry. However, realizing this potential requires a concerted effort to address the existing challenges, foster innovation, and develop regulatory frameworks that support sustainable growth. This study represents a step in that direction, providing a foundation for future research and development initiatives aimed at harnessing the power of AI and ST in transforming offsite construction.

2. DATA AND METHODS

To ensure a comprehensive review, a systematic literature review was conducted with databases searched, including Google, Scopus, Web of Science, IEEE Xplore, and Google Scholar. The search queries used were "Artificial Intelligence in Offsite Construction," "Smart Technologies in Offsite Construction," "Machine Learning in Prefabrication," and "Deep Learning Algorithms." The subsequent methodology used involved literature research, a preliminary analysis, and a literature selection of approximately 150 articles potentially relevant to the current status. A detailed analysis and classification by categorizing subfields of AI (e.g., machine learning, robotics) and types of smart technologies (e.g., drones, IoT devices) is presented in Figure 1.

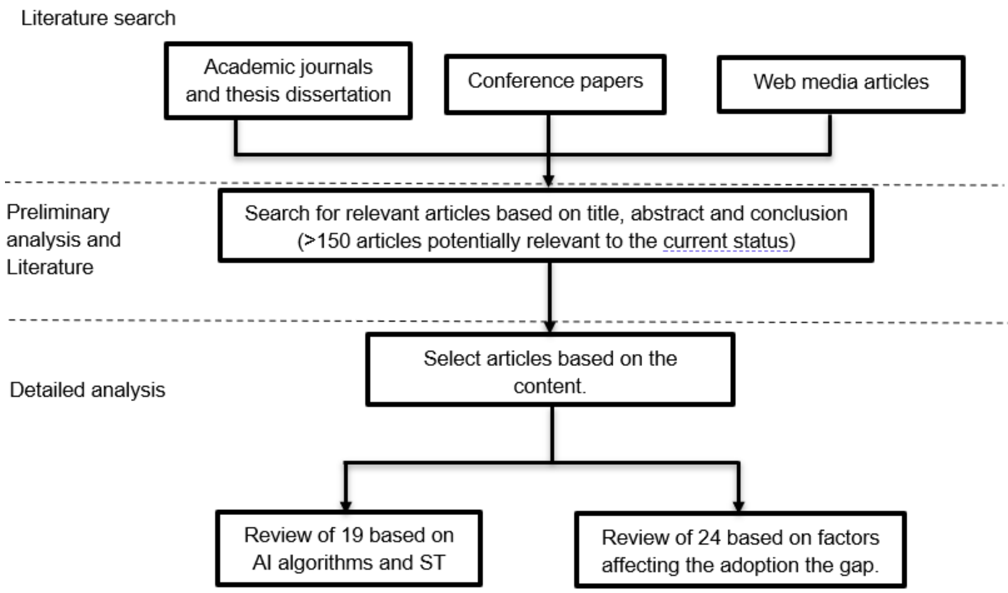

Figure 1: Schematic representation of the methodology

3. THEORETICAL FRAMEWORK

Theoretical frameworks are essential in research as they provide a structured lens through which studies can be conducted and understood. In the context of Artificial Intelligence (AI), theories often address the nature of intelligence in humans, computers, and other entities, encompassing a broad spectrum of intelligences including human (natural) intelligence, computer (artificial) intelligence, and collective (group) intelligence, among others. Theories in AI are concerned with understanding and replicating the cognitive abilities of humans and other forms of intelligence in computational systems.

In mainstream AI research, projects are typically guided by practical problem-solving demands, insights from the study of human intelligence, and normative models that provide a theoretical basis for system design and analysis. The theory of computation, for example, is often applied to AI projects to address practical computational problems. Insights from psychology and neuroscience are used to model and understand human-like intelligence in AI systems. Normative models, such as those based on classical logic and probability theory, are used to design, and analyze AI systems in a rigorous and formal manner.

However, this study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), which is a model that explains the acceptance and use of technology. Developed by (Venkatesh et al., 2003), UTAUT synthesizes and extends eight prominent models from the technology acceptance literature: the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Motivational Model (MM), the combined TAM and TPB (C-TAM-TPB), the Model of PC Utilization (MPCU), the Diffusion of Innovations Theory (DOI), and the Social Cognitive Theory (SCT).

UTAUT posits four key constructs that directly influence technology acceptance and usage behavior:

I. Performance Expectancy: The degree to which an individual believes that using technology will help them to perform better.
II. Effort Expectancy: The ease of use associated with technology.
III. Social Influence: The degree to which an individual perceives that important others believe they should use the technology.
IV. Facilitating Conditions: The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology.

These constructs are moderated by individual characteristics such as gender, age, experience, and voluntariness of use. Subsequent extensions to the UTAUT model have introduced additional constructs such as hedonic motivation, price value, and habit, which further explain technology acceptance and use.

4. APPLICATION OF AI AND SMART TECHNOLOGIES IN OFFSITE CONSTRUCTION

As depicted Figure 2, Machine Learning (ML) is a branch of AI where computers analyze data to create models that can solve problems. Unlike traditional programming, which relies on explicitly coded rules, ML uses data to develop predictive models for making forecasts on new, unseen data. Deep Learning (DL), a subset of ML, focuses on Artificial Neural Networks (ANN) and related algorithms with multiple hidden layers, resulting in a multi-step computation process from input to output. On the other hand, ST in offsite construction encompass a range of tools and systems that enhance the capabilities of construction professionals and improve the overall efficiency of construction projects.

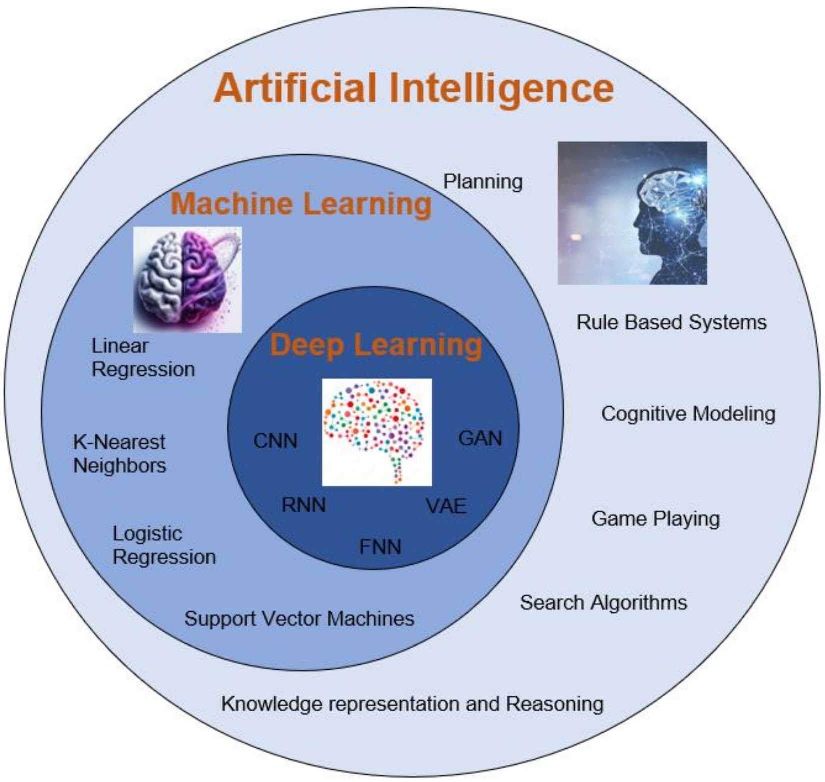

Figure 2: Schematic representation of AI, ML and DL algorithms in off-site construction

Figure 3: Smart technology functionality in offsite construction

4.1 Machine Learning Algorithms:

- **k-Nearest Neighbors (k-NN)**: k-NN algorithm is used for classification and regression tasks in offsite construction. For example, it can predict project outcomes like delays or cost overruns based on historical data of similar past projects. The algorithm finds the *k* closest data points (neighbors) in the training dataset to the new data point and predicts the outcome based on the majority class/average value of those neighbors. Euclidean distance is usually used to find nearest neighbors (Lee et al., 2017). For arbitrary example *x*, a multidimensional feature vector $[a_1(x), a_2(x), \cdots, a_n(x)]$ is used, with $a_r(x)$ representing the *r*th attribute value.
  The Euclidean distance between x_i and x_j is calculated using the formula: $Dis(x_i, x_j) = \sqrt{\sum_{r=1}^{r=n}[a_r(x_i) - a_r(x_j)]^2}$
- **Logistic Regression:** Utilized for binary classification problems, such as determining the likelihood of project delays. It models the probability of an event occurring (e.g., project delay) based on the input features.
  The logistic regression formula is: $P(y = 1|x) = 1 \,/\, \left(1 + e^{-(b_0+b_1\times x_1 t b_2\times k+\cdots+ln\times x_n)}\right)$
  Where *y* is the binary outcome (e.g., delay or no delay), x_1, x_2, ..., x_n are the input features (e.g., project size, team experience), and b_0, b_1, ..., b_n are the coefficients learned from the training data (Cheng et al., 2010; Hosmer Jr et al., 2013).

- **Linear Regression**: It is applied for predicting continuous outcomes, such as cost estimations and resource allocation. It models the relationship between the input features and the continuous target variable as a linear equation: $y = b_0 + b_1 \times x_1 + b_2 \times x_2 + \cdots + b_n \times x_n$.
  Where *y* is the continuous target variable (e.g., project cost), $x_1, x_2, ..., x_n$ are the input features (e.g., project size, material costs), and $b_0, b_1, ..., b_n$ are the coefficients learned from the training data (Ibragimov et al., 2022; Merry et al., 2021).
- **Support Vector Machines (SVM):** SVMs are effective for classification and regression problems in offsite construction. They can identify patterns in data and make predictions about project timelines and resource needs. For instance, an SVM model can be trained on historical data to classify whether a project will be completed within the planned timeline or not, based on features like project size, team experience, and resource availability.
  The SVM algorithm finds the optimal hyperplane that maximizes the margin between the classes, given by the formula: $w^T x + b = 0$, where *w* is the normal vector to the hyperplane, *x* is the input data point, and b is the bias term (Campbell & Ying, 2022; Moguerza & Muñoz, 2006).
- **Neural networks** are used for complex pattern recognition and predictive analytics in offsite construction, enhancing decision-making processes. They can model non-linear relationships between input features and target variables, making them suitable for tasks like predicting project risks, optimizing resource allocation, and identifying potential issues or defects. The output of a neural network is calculated as: $y = f(w^T x + b)$. Where x is the input vector, *w* is the weight matrix, *b* is the bias vector, and *f* is the activation function (e.g., sigmoid, ReLU) that introduces non-linearity (Madhu et al., 2023).

4.2 Deep Learning Algorithms

- **Feedforward Neural Networks (FNN)** are the simplest type of Artificial Neural Network (ANN). They consist of an input layer, one or more hidden layers, and an output layer. Each neuron in a layer is connected to every neuron in the next layer, and the information moves in one direction—from input to output (Yang et al., 2024). FNNs are used for tasks such as predicting project costs, resource allocation, and identifying potential risks.
- **Convolutional Neural Networks (CNNs)**: CNNs are specialized neural networks designed for processing structured grid data, such as images. They use convolutional layers to automatically and adaptively learn spatial hierarchies of features from input images (Figure 4) (Convolutional, 2024).

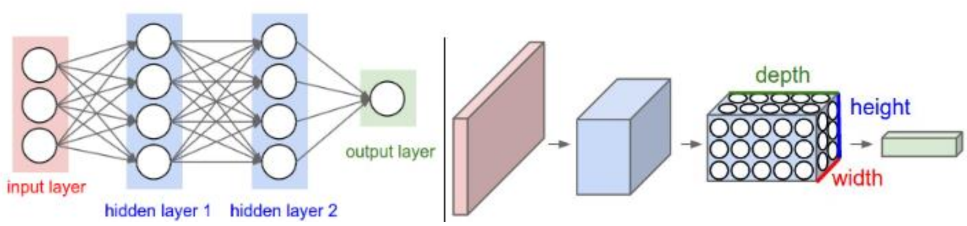

Figure 4. A 3-layer Neural Network (left), A CCN in three dimensions (Convolutional, 2024).

  CNNs are used to identify and track construction progress, detect defects, and monitor safety compliance through image and video analysis. For instance, CNN can be used to monitor the progress of a construction project by analyzing images captured by drones. The network can identify different stages of construction and detect any deviations from the planned schedule.
  The output of a convolutional layer is given by: $y_{i,j,k} = f\left(\Sigma_{m,n,l} x_i + m, j + n, l \times W_{m,n,l,k} + b_k\right)$. where: *x* is the input image, *w* is the filter (kernel), *b* is the bias, f is the activation function, and i, j, k are the indices of the output feature map.
- **Generative Adversarial Networks (GAN)**: GANs consist of two neural networks—the generator and the discriminator—that are trained simultaneously through adversarial processes. The generator creates fake data samples, while the discriminator evaluates their authenticity. For example, a GAN can be trained on a dataset of architectural floor plans to generate new, realistic

floor plans that adhere to specific design criteria. This can help architects quickly explore various design options.

The objective of a GAN is to solve the following minimax game: min*G* max*D V(D,G)*=Ex~*pdata* (x) [logD(x)] +Ez~*pz* (z) [log(1-D(G(z)))]. Where: G is the generator, D is the discriminator, *pdata* is the data distribution, and *pz* is the prior distribution of the input noise z (Liu, 2022).

- **Variational Autoencoders (VAE)**: Used for generating new data samples and improving design optimization. VAEs are generative models that learn to encode input data into a latent space and then decode it back to the original space. They introduce a probabilistic approach to encoding, which allows for the generation of new data samples. A VAE can be used to generate different versions of a building layout by sampling from the latent space. This helps in optimizing the design for various criteria such as space utilization and aesthetic appeal.
  The loss function for a VAE is given by: $\mathcal{L} = E_{q(z|x)}[log\, p(x|z)] - D_{KL}\left(q(z|x)|p(z)\right)$. Where: $q(z|x)$ is the encoder, $p(x|z)$ is the decoder, D_{KL} is the Kullback-Leibler divergence (Yan et al., 2020).
- **Recurrent Neural Networks (RNN):** Effective for time-series predictions, such as forecasting project timelines and resource needs. RNNs are designed to handle sequential data by maintaining a hidden state that captures information from previous time steps. They are particularly effective for time-series predictions. An RNN can be used to predict the timeline of a construction project by analyzing past project schedules and identifying patterns that lead to delays. This helps project managers take proactive measures to stay on schedule.
  The hidden state h_t of an RNN at time step t is given by: $h_t = f(w_h h_{t-1} + w_x x_t + b)$. Where: w_h and w_x are weight matrices, x_t is the input at time step t, b is the bias, f is the activation function (e.g., hyperbolic tangent (tanh), Rectified Linear Unit (ReLU)) (Colah, 2024).

4.2 Smart Technologies in Offsite Construction

- **Building Information Modeling (BIM):** BIM can facilitate better collaboration among architects, engineers, and contractors by providing a shared digital representation of a project (Babalola et al., 2023). This leads to more accurate planning, reduced errors, and efficient execution of construction projects. In addition, with the integration of AI in software such as Autodesk Revit and Navisworks (developed by Autodesk), AI algorithms can analyze BIM data to predict potential issues, optimize resource allocation, and enhance design efficiency.
- **Internet of Things (IoT) devices**: IoT devices collect real-time data on various aspects of the construction process, from equipment conditions to environmental factors. This data helps optimize workflows, predict maintenance needs, and enhance safety compliance, leading to more efficient and safer construction sites (Solanki et al., 2024). For instance, wearable sensors like smart helmets and vests (e.g., from companies like DAQRI) can monitor workers' health and safety in real-time in offsite construction while Radio Frequency Identification (RFID) is used to attach and track prefabricated materials and provide storing information.
- **Digital Twins**: Digital twins offer a comprehensive view of construction projects, allowing for real-time monitoring and management. They help optimize construction processes, improve decision-making, and reduce the risk of errors and delays (Energy, 2024). Some examples of digital twin solutions are the Siemens Digital Twin, which provides a virtual representation of physical assets and processes, enabling real-time monitoring and management, and the GE Digital Twin, which can be used for predictive maintenance and operational optimization in construction projects. GE's Network Digital Twin provides a comprehensive view of the grid by combining Geographic Information Systems (GIS), Energy Management Systems (EMS), and Advanced Distribution Management Systems (ADMS).
- **Augmented Reality (AR):** AR is used for visualization of prefabricated components and defect management, enhancing the accuracy and efficiency of construction processes. Some software such as Microsoft HoloLens (developed by Microsoft), which is used for design visualization and on-site construction assistance, and ARki (developed by Darf Design) allow designers to create 3D models and superimpose them on real-world environments (Mirindi et al., 2024).
- **Blockchain Technology**: Blockchain solutions such as IBM Blockchain (developed by IBM) ensure secure transactions, transparent logistics, and reliable smart contracts, improving trust

and efficiency in construction projects. It reduces the risk of fraud and enhances accountability among stakeholders (Sati & Al-Tabtabai, 2024).

- **Drones and Aerial Imaging**: Drones, or Unmanned Aerial Vehicles (UAVs), enhance the accuracy and efficiency of construction planning and monitoring. They provide detailed site surveys, real-time data collection, digital localization with the Global Positioning System (GPS), and 3D modeling, reducing the need for manual inspections and improving project oversight. DJI Phantom (developed by DJI) is one of the popular drones used for site surveys and data collection, while Pix4D is a software that processes drone-captured images to create detailed 3D models (Mirindi et al., 2024).
- **Wearable Technologies**: Wearable technologies monitor worker safety and productivity, providing real-time data to improve site management and safety compliance. They enhance worker well-being and reduce the risk of injuries on construction sites. Some examples are Smart Helmets (e.g., from DAQRI) equipped with sensors to monitor worker health and safety, and Exoskeletons (e.g., from companies like Sarcos Robotics), which are wearable devices that enhance worker strength and reduce fatigue (Patel et al., 2022).
- **Robotics in Offsite Construction**: Robotics in offsite construction automates repetitive and labor-intensive tasks, improving efficiency and precision. Robots can work in controlled environments, reducing the risk of errors and enhancing the quality of prefabricated components. AI-powered robots (e.g., from companies like KUKA Robotics and Boston Dynamics) can adapt to changing conditions, optimize resource usage, and ensure consistent quality in construction projects (Sandy, 2018).

5. ETHICAL ISSUES IN OFFSITE CONSTRUCTION

The integration AI and ST in offsite construction brings five ethical considerations that are critical to address. These concerns include ensuring data quality, reliability, and accuracy, transparency and accountability, and ethical governance and moral responsibility. In addition, cybersecurity measures are essential to protect sensitive information, and the potential for job displacement necessitates careful consideration and management.

To align with ethical standards, the application of AI in offsite construction should adhere to the Unified Theory of Acceptance and Use of Technology (UTAUT) principles, which emphasize the importance of performance expectancy, effort expectancy, social influence, and facilitating conditions. Additionally, the correctness, concreteness, and compactness criteria for AI theories, as noted by (Wang, 2012), should guide the development and application of these technologies.

Addressing these ethical issues requires a concerted effort to increase research, development, and investment in AI and ST. This includes establishing and enforcing regulatory frameworks and standards to ensure ethical practices and reduce the incidence of related issues. Standardization is particularly important for ethical integration in both offsite and onsite construction contexts.

The key ethical considerations include:

I. Data Quality, Reliability, and Accuracy: In offsite construction, the integrity of AI-driven decisions is heavily dependent on the quality, reliability, and accuracy of the data used. AI systems, particularly in areas like automated planning and scheduling, optimization, and machine learning, require precise and high-quality data to function effectively. Poor data can lead to flawed outcomes, such as incorrect construction plans, inefficient resource allocation, or safety risks due to inaccurate predictions or assessments. Ensuring data quality involves rigorous data collection, validation, and cleaning processes. Reliability and accuracy must be maintained through continuous monitoring and updating of data sets to reflect the true state of the construction environment (Abioye et al., 2021; Aimultiple, 2024). This is important for maintaining the trust of stakeholders and ensuring that the automated processes result in beneficial outcomes without compromising safety or efficiency in offsite construction projects.

II. Transparency and Accountability: The development and deployment of AI in construction must be transparent, with clear accountability for decisions made by AI systems. This ensures that there is trust in technology and that ethical standards are maintained (Observer, 2024).

III. Privacy and Data Protection: With the vast amounts of data collected by AI and IoT devices, it is crucial to handle and analyze personal and sensitive information properly, respecting privacy laws and ethical considerations (Clarke, 2024).
IV. Employment and Human Welfare: AI should be viewed as a tool that empowers rather than replaces human workers. The industry must manage the balance between improving productivity and maintaining job security, ensuring that technology does not come at the expense of human well-being (McAleenan, 2020; Observer, 2024).
V. Ethical Governance and Moral Responsibility: Establishing ethical governance is essential to build trust in AI systems. This includes addressing the moral responsibilities of developers and users of AI technology to prevent unintended harm and ensure the safety and well-being of all stakeholders in the construction process (McAleenan, 2020).

6. ADVANTAGES, DISADVANTGES OF AI and ST IN OFFSITE CONSTRUCTION

Integrating AI and ST in offsite construction is fraught with challenges, including cultural, political, legal, and economic barriers, as well as cybersecurity threats, high costs, and connectivity issues. Negative attitudes, misconceptions, and data security concerns further complicate the integration process in the Australian construction industry, as noted by (Regona et al., 2022). The need for large, accurate datasets for AI algorithms is a significant hurdle, often costly and time-consuming, contributing to the reluctance of firms to move away from traditional methods. High costs, skill shortages, and inadequate training are additional obstacles, with the complexity of the construction ecosystem and the volume of on-site data adding to the difficulties.

Table 1 outlines the advantages and disadvantages of various AI subfields in offsite construction, providing a clearer picture of the potential and limitations of these technologies. Machine Learning offers predictive insights and efficiency but is limited by data completeness and model scalability. Computer Vision accelerates monitoring and improves accuracy but struggles with scene comprehension and action recognition. Automated Planning and Scheduling can lead to cost and time savings, yet the complexity and cost of implementation are barriers. Robotics improves productivity and safety but comes with high initial costs and the risk of job displacement. Knowledge-based Systems facilitate information access and consistency but face intellectual property and knowledge acquisition challenges. Natural Language Processing aids in time management and communication but has difficulties with language complexity and data privacy. Lastly, Optimization increases operational efficiency but requires significant computing power and has scalability issues. These subfields have the potential to transform construction practices, but their effective integration requires overcoming the outlined challenges.

Table 1: Advantages and Disadvantages of AI and ST in Offsite Construction

Subfield	Advantages	Limitations	Sources
Knowledge-based Systems	Access to information, update ease, solution explanation, consistency, incomplete information handling.	Intellectual property, knowledge acquisition, validation issues.	(Alavi & Leidner, 1999)
Automated machinery and systems	Cost savings, productivity, reduced planning effort, simplified control, optimal plans.	Costly, complex, knowledge representation issues.	(Ghallab et al., 2004)
Predictive and decision-support algorithms	Predictive insights, efficiency, cost savings, safety, resource utilization, fewer mistakes.	Incomplete data, scalability of models.	(Kotsiantis et al., 2007)
Intelligent databases and expert systems	Productivity, safety, quality, reliability, consistency.	High initial costs, job loss, unstructured environments.	(Seo et al., 2015)
Linguistic data interpretation and processing	Time management, communication, cost-effectiveness.	Language representation, speech recognition, data privacy.	(Bates & Weischedel, 1993)

Strategic problem-solving and efficiency enhancement	Operations, efficiency, productivity, time management, cost savings.	Computing power, scalability.	(Roy et al., 2008)
Digital image analysis	Faster monitoring, accuracy, transparency, cost-effective, productivity, safety.	Scene understanding, action recognition, tracking accuracy.	(Seo et al., 2015)

7. CURRENT AND FUTURE OPPORTUNITIES

Offsite construction, a subset of the broader construction industry, is increasingly adopting AI and Smart ST to enhance efficiency, safety, and innovation. This segment of the industry focuses on the planning, design, fabrication, and assembly of building elements at a location other than their final site of installation. The use of offsite construction methods is growing due to its potential for reducing waste, improving quality control, and shortening construction timelines. Table 2 highlights how AI and ST are integral to the evolution of offsite construction. In Waste Management for example, AI's role in efficient waste handling is crucial for offsite construction, where materials are pre-measured and cut, necessitating precise waste quantification to minimize excess. The prospective AI-driven holistic waste analytics tools will likely further reduce waste and improve sustainability in offsite construction practices. Service Value Enhancement through AI in offsite construction involves accurate cost and schedule estimations, which are vital for the prefabrication processes that require meticulous planning and coordination. The potential use of deep learning could lead to even more accurate predictions, streamlining the offsite construction workflow.

On the other hand, Employment Creation in offsite construction is influenced by automation, which is expected to create specialized roles such as developers, trainers, and testers for construction automation tools. These roles are essential for managing the complex machinery and software used in offsite manufacturing facilities. While Industry 4.0's integration with BIM and IoT is particularly relevant to offsite construction, where energy management and smart construction practices can be monitored and adjusted in real-time, even from remote locations. In addition, in Smart Urban Development, AI's application to safety on construction sites and smart sensors for urban planning aligns with offsite construction's need for precision and planning. Future analytics tools will likely enhance the planning and integration of offsite-constructed elements into smart city infrastructures.

Table 2: Current and Future Opportunities

Sub-domain in offsite Construction	Present Advancements	Prospective Developments	Sources
Waste Management	Utilization of AI for efficient waste handling and quantification, BIM frameworks to reduce waste	AI-driven holistic waste analytics tool	(Azoai, 2024)
Service Value Enhancement	AI applications for precise cost and schedule estimation, BIM for site analytics	Deep learning for cost and time estimation, AI-driven BIM-based construction site analytics	(Joist, 2024)
Employment Creation	Impact of automation on job creation, AI for skill enhancement	Construction automation tools developer, systems trainers, systems testers	(Constructiondive, 2024a)
Industry 4.0 Integration	BIM integrated with IoT for energy management, AI for smart construction	AI-driven IoT platform, AI-enabled BIM for IoT	(Pan & Zhang, 2023; Weforum, 2024)
Smart Urban Development	AI for safety on construction sites, smart sensors for urban planning	AI-driven built environment analytics, Interoperable building management systems (BMS)	(Joist, 2024)

AR in Construction	BIM and AR for defect management, ontology-based data collection	AI-enabled visual exploration system, AI and AR-based virtual site exploration	(Azoai, 2024)
Blockchain Technology	Blockchain for logistics, smart contracts in construction	Secure and transparent AI-driven solutions to improve trust	(Linkedin, 2024)
Quantum Computing	Exploration of quantum computing in AI solutions	QC optimization of existing AI solutions, QC and AI-driven BIM data analytics	-
Supply Chain Management	AI for risk monitoring and supply chain optimization	AI with blockchain for construction supply chain management	(Joist, 2024)
Safety and Health Analytics	BIM for hazard identification, AI for safety risk reviews	AI chatbot for supply chain, AI deep learning for predictive health and safety analytics	(Joist, 2024; Weforum, 2024)
Contract Administration	AI support for construction contract management	AI-driven construction contract analytics	(Constructiondive, 2024a)
Voice Interaction	Voice-activated commands for construction tasks	AI-driven voice user interfaces for use in design, onsite and offsite construction activities	(Azoai, 2024)
Financial Auditing	BIM for cost management in construction	AI-driven audit system for construction financials	(Constructiondive, 2024b)
Design Optimization	AI for generative design and design optimization	AI for parametric design and automated design refinement	(Azoai, 2024)
Autonomous Construction Robotics	AI-driven robots for assembly and construction tasks	Fully autonomous AI-managed offsite construction facilities	(Joist, 2024)

However, AR in Construction, Blockchain Technology, Quantum Computing, and Supply Chain Management are other areas where AI and ST are set to revolutionize offsite construction. AR can assist in visualizing prefabricated components, blockchain can secure transactions and logistics, quantum computing can optimize complex computations, and AI can streamline supply chain management. Finally, Safety and Health Analytics, Contract Administration, Voice Interaction, Financial Auditing, Design Optimization, and Autonomous Construction Robotics are additional sub-domains where AI and ST advancements are expected to optimize and automate offsite construction processes. These technologies will contribute to the creation of safer, more efficient, and cost-effective offsite construction methods.

In summary, the integration of AI and ST in offsite construction is leading to a transformation in how buildings are designed, fabricated, and assembled. The advancements and future opportunities outlined indicate a shift towards a more digital, precise, and sustainable construction process, with offsite construction at the forefront of this change.

8. CONCLUSION

This comprehensive review explores the integration of Artificial Intelligence (AI) and Smart Technologies (ST) in offsite construction, highlighting their potential to redefine industry standards. Anchored in the Unified Theory of Acceptance and Use of Technology (UTAUT), this study examines the current landscape and future possibilities of AI and ST in enhancing offsite construction methods. The analysis discusses the benefits of AI and ST, such as improved efficiency, safety, and innovation, while acknowledging the challenges of cultural resistance, security concerns, and initial investments. The review emphasizes the importance of Building Information Modeling (BIM) and other technological advancements in refining construction processes, from conceptual design to monitoring. The application of machine learning (ML) algorithms, including k-Nearest Neighbors (k-NN), logistic regression, linear regression, Support Vector Machines (SVM), and neural networks, as well as Deep Learning (DL) algorithms like feedforward neural Networks (FNN), Convolutional Neural Networks (CNN), Generative Adversarial Networks (GANs), variational autoencoders (VAE), and Recurrent Neural Networks (RNN), shows promise in improving various aspects of offsite construction, including project management, quality assurance, and safety surveillance. However, the review also identifies areas for further research and development. It calls for continued research to unlock the full potential of AI and ST in offsite construction. Establishing regulatory frameworks and standards is important for ethical integration and mitigating security risks. Additionally, addressing the shortage of skilled talent and providing robust training for the workforce are essential for overcoming the challenges posed by these advanced technologies. Based on these insights, the study proposes strategic research and development initiatives to bridge the gaps in the deployment of AI and ST in offsite construction. Collaboration between scholars, industry practitioners, and policymakers is vital for leveraging the advantages of these technologies and driving sustainable progress in the construction sector. The future of offsite construction looks promising, with AI and ST leading the way towards more innovative, efficient, and secure construction practices.

References

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. Journal of Building Engineering, 44, 103299.

Aimultiple, R. (2024). https://research.aimultiple.com/data-quality-ai/.

Alavi, M., & Leidner, D. (1999). Knowledge management systems: issues, challenges, and benefits. Communications of the Association for Information systems, 1(1), 7.

Ali Hassony, H., & Ahmed, A. L. (2024). Reviewing applications of digital twins in building management in response to the Covid-19 pandemic. AIP Conference Proceedings,

Azoai. (2024). https://www.azoai.com/article/The-Impact-of-AI-on-Construction.aspx.

Babalola, A., Musa, S., Akinlolu, M. T., & Haupt, T. C. (2023). A bibliometric review of advances in building information modeling (BIM) research. Journal of Engineering, Design and Technology, 21(3), 690-710.

Bates, M., & Weischedel, R. M. (1993). Challenges in natural language processing. (No Title).

Campbell, C., & Ying, Y. (2022). Learning with support vector machines. Springer Nature.

Cheng, M.-Y., Peng, H.-S., Wu, Y.-W., & Chen, T.-L. (2010). Estimate at completion for construction projects using evolutionary support vector machine inference model. Automation in Construction, 19(5), 619-629.

Chugh, V., Basu, A., Kaushik, A., Bhansali, S., & Basu, A. K. (2024). Employing nano-enabled artificial intelligence (AI)-based smart technologies for prediction, screening, and detection of cancer. Nanoscale.

Clarke, O. (2024). https://www.osborneclarke.com/insights/ais-potential-key-risks-construction-industry.

Colah. (2024). https://colah.github.io/posts/2015-08-Understanding-LSTMs/.

Constructiondive. (2024a). https://www.constructiondive.com/news/will-ai-take-my-construction-job-only-if-you-want-robots-automated/650255/.

Constructiondive. (2024b). https://www.constructiondive.com/spons/bim-services-a-game-changer-for-mep-engineers-and-consultants/710579/.

Convolutional. (2024). https://cs231n.github.io/convolutional-networks/.

Energy, A. W. (2024). Edge driven Digital Twins in distributed energy systems.

Ghallab, M., Nau, D., & Traverso, P. (2004). Automated Planning: theory and practice. Elsevier.

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression. John Wiley & Sons.

Ibragimov, M., Khujaev, O., Rakhimboev, H., & Khaitboeva, D. (2022). Modeling Using Linear and Polynomial Regression Algorithms of Machine Learning Based on Mahalla Data. Евразийский журнал математической теории и компьютерных наук, 2(14), 58-65.

Joist. (2024). https://www.joist.ai/post/constructing-the-future-how-the-construction-industry-is-embracing-ai.

Kotsiantis, S. B., Zaharakis, I., & Pintelas, P. (2007). Supervised machine learning: A review of classification techniques. Emerging artificial intelligence applications in computer engineering, 160(1), 3-24.

Lee, K.-P., Lee, H.-S., Park, M., Kim, D. Y., & Jung, M. (2017). Management-reserve estimation for international construction projects based on risk-informed k-NN. Journal of Management in Engineering, 33(4), 04017002.

Linkedin. (2024). https://www.linkedin.com/advice/1/what-current-trends-future-opportunities-offsite.

Liu, H. (2022). Generative Adversarial Learning Using Optimal Transport State University of New York at Stony Brook].

Madhu, G., Kautish, S., Alnowibet, K. A., Zawbaa, H. M., & Mohamed, A. W. (2023). Nipuna: A novel optimizer activation function for deep neural networks. Axioms, 12(3), 246.

McAleenan, P. (2020). Moral responsibility and action in the use of artificial intelligence in construction. Proceedings of the Institution of Civil Engineers-Management, Procurement and Law, 173(4), 166-174.

Merry, M., Riddle, P., & Warren, J. (2021). A mental models approach for defining explainable artificial intelligence. BMC Medical Informatics and Decision Making, 21, 1-12.

Mirindi, D., Mirindi, F., & Oshineye, O. (2024). Navigating Construction Project Outcomes: Synergy through the Evolution of Digital Innovation and Strategic Management. International Journal of Latest Research in Engineering and Technology (IJLRET), 10(03), 17-25. https://doi.org/10.56581/IJLRET.10.3.17-25

Moguerza, J. M., & Muñoz, A. (2006). Support vector machines with applications.

Observer, C. (2024). https://commercialobserver.com/2024/02/ai-construction-ethics/.

Pan, M., Yang, Y., Zheng, Z., & Pan, W. (2022). Artificial intelligence and robotics for prefabricated and modular construction: a systematic literature review. Journal of construction engineering and management, 148(9), 03122004.

Patel, V., Chesmore, A., Legner, C. M., & Pandey, S. (2022). Trends in workplace wearable technologies and connected-worker solutions for next-generation occupational safety, health, and productivity. Advanced Intelligent Systems, 4(1), 2100099.

Regona, M., Yigitcanlar, T., Xia, B., & Li, R. Y. M. (2022). Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. Journal of open innovation: technology, market, and complexity, 8(1), 45.

Roy, R., Hinduja, S., & Teti, R. (2008). Recent advances in engineering design optimisation: Challenges and future trends. CIRP annals, 57(2), 697-715.

Sanders, N. R., & Wood, J. D. (2024). The Humachine: AI, Human Virtues, and the Superintelligent Enterprise. Taylor & Francis.

Sandy, T. (2018). High-Accuracy Mobile Manipulation for On-Site Robotic Building Construction ETH Zurich].

Sati, A., & Al-Tabtabai, H. (2024). A paradigm shift toward the application of blockchain in enhancing quality information management. Construction Innovation, 24(1), 407-424.

Seo, J., Han, S., Lee, S., & Kim, H. (2015). Computer vision techniques for construction safety and health monitoring. Advanced Engineering Informatics, 29(2), 239-251.

Solanki, A., Sarkar, D., & Shah, D. (2024). Evaluation of factors affecting the effective implementation of Internet of Things and cloud computing in the construction industry through WASPAS and TOPSIS methods. International Journal of Construction Management, 24(2), 226-239.

Taheri, H., Gonzalez Bocanegra, M., & Taheri, M. (2022). Artificial intelligence, machine learning and smart technologies for nondestructive evaluation. Sensors, 22(11), 4055.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS quarterly, 425-478.

Wang, P. (2012). Theories of artificial intelligence—Meta-theoretical considerations. In Theoretical foundations of artificial general intelligence (pp. 305-323). Paris: Atlantis Press.

Weforum. (2024). https://www.weforum.org/agenda/2023/06/4-ways-ai-is-revolutionising-the-construction-industry/.

Yan, C., Wang, S., Yang, J., Xu, T., & Huang, J. (2020). Re-balancing variational autoencoder loss for molecule sequence generation. Proceedings of the 11th ACM international conference on bioinformatics, computational biology and health informatics,

Yang, B., Liang, B., Qian, Y., Zheng, R., Su, S., Guo, Z., & Jiang, L. (2024). Parameter identification of PEMFC via feedforward neural network-pelican optimization algorithm. Applied Energy, 361, 122857.