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Generative AI, Large Language Models, and ChatGPT in Construction Education, Training, and Practice

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Abstract: The rapid advancement of generative AI, large language models (LLMs), and ChatGPT presents transformative opportunities for the construction industry. This study investigates their integration across education, training, and professional practice to address skill gaps and inefficiencies. While AI's potential in construction has been highlighted, limited attention has been given to synchronising academic curricula, workforce development, and industry practices. This research seeks to fill that gap by evaluating AI adoption through a mixed and multi-stage methodology, including theoretical conceptualisation, case studies, content analysis and application of strategic frameworks such as scenario planning, SWOT analysis, and PESTEL frameworks. The findings show AI tools enhance foundational learning and critical thinking in education but often fail to develop job-ready skills. Training programmes improve task-specific competencies with immersive simulations and predictive analytics but neglect strategic leadership skills. Professional practice benefits from AI-driven resource optimisation and collaboration tools but faces barriers like regulatory and interoperability challenges. By aligning theoretical education with practical training and strategic professional development, this research highlights the potential to create a future-ready workforce. The study provides actionable recommendations for integrating AI across domains. These findings contribute to understanding AI's transformative role in construction, offering a baseline for effective and responsible adoption.

Keywords: generative AI; large language models; ChatGPT; construction education; training; practice; construction management; automation; digitisation

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1. Introduction

The construction industry, traditionally reliant on labour-intensive processes and fragmented workflows, is undergoing a transformative shift with the integration of advanced digital technologies. This shift is collectively known as Construction 4.0 and refers to the digital transformation of the construction industry, integrating advanced technologies such as Building Information Modelling (BIM), robotics, automation, Internet of Things (IoT), artificial intelligence (AI), and digital twin technologies to enhance productivity, efficiency, and sustainability in construction workflows [1,2]. Among these advancements, generative artificial intelligence (AI) and large language models (LLMs) such as ChatGPT have emerged as transformative tools that promise to revolutionise education, training, and practice in the construction sector [3–5]. These tools have already demonstrated their potential in other industries by generating human-like text, analysing large datasets, and supporting multilingual communication. These capabilities have direct relevance for the construction industry [6]. For instance, OpanAI's ChatGPT (GPT-4V) and its different engines and versions has been used to automate project documentation, enhance safety training through real-time simulations, and optimise workflows by bridging language and cultural barriers in global projects [7–9]. In education, generative AI supports personalised learning experiences, helping students and professionals develop critical skills in construction management and engineering [10,11]. Despite these advantages, the adoption of generative AI in construction remains limited due to challenges such as a lack of industry-specific AI models, fragmented and unstructured data, regulatory concerns, and limited real-time applicability. For example, while Generative AI can generate architectural concepts, it struggles to incorporate structural and material constraints, requiring manual adjustments by engineers. Similarly, AI-generated construction schedules often fail to account for project-specific disruptions, limiting their reliability in practice. Additionally, AI-generated documentation, such as risk assessments and contracts, faces legal barriers requiring human oversight. These limitations create a disconnect between educational training in AI-driven methodologies and the actual capabilities and constraints faced in professional construction practice, highlighting the need for AI-integrated curricula and industry-focused training programs and practices.

This research is driven by a problem that the construction industry continues to face persistent challenges in adopting advanced technologies, including skill shortages, inefficiencies in training processes, and fragmented professional workflows. The lack of AI-trained professionals limits the implementation of AI-enhanced BIM and predictive analytics, leaving many AI tools underutilised. Accordingly, this research is driven by the following overarching question: How can Generative AI, LLMs, and ChatGPT be systematically integrated into construction education, workforce training, and professional workflows to address skill gaps, optimise training methodologies, and enhance operational efficiency [12,13]? There are discrepancies between the skills being taught in educational and training programs and the actual requirements of practice. Workforce training remains inefficient, with most programs still relying on traditional methods rather than AI-driven simulations or real-time predictive safety models [14–16]. Additionally, fragmented workflows across construction stakeholders hinder seamless AI integration, making it difficult to automate scheduling, risk assessment, and real-time decision-making. Addressing these challenges requires structured AI training, improved digital collaboration frameworks, and industry-wide adoption of AI-enhanced construction workflows. Hence, while generative AI and LLMs offer transformative potential, their application in construction education, training, and practice lacks comprehensive exploration and practical guidance.

The significance and timeliness of this study lie in its focus on bridging the gaps between AI education, industry practice, and workforce development. By systematically evaluating AI's capabilities, constraints, and strategic implementation pathways, this research contributes to the sustainable and ethical adoption of AI technologies—a critical component of Construction 4.0 and the evolution towards Construction 5.0. This study advances the body of knowledge by providing actionable insights that support scalable and practical AI adoption while addressing concerns such as AI ethics, workforce transformation, and digital integration challenges [17,18].

The novelty of this study lies in its comprehensive, cross-domain examination of Generative AI applications, demonstrating how these tools can: enhance educational outcomes through AI-driven adaptive learning and intelligent tutoring systems. The outcomes can also assist in refining workforce training methodologies using immersive simulations, predictive safety modelling, and real-time AI-powered instruction. Accordingly, lending to optimise professional workflows by improving decision-making, automating compliance tracking, and facilitating digital collaboration across project stakeholders. By integrating comparative case study analysis with strategic assessment frameworks, this research provides a holistic and practically relevant exploration of AI's transformative role in construction, offering insights that are valuable to academics, industry practitioners, and policymakers.

2. Background

The integration of digital technologies into the construction industry has been a transformative journey, marked by milestones that highlight the steady progression of research and innovation. The development of Building Information Modelling (BIM) in the early 2000s laid the foundation for integrating digital workflows in construction [19–21]. During the mid-2000s, the focus shifted to exploring the role of automation and artificial intelligence (AI) in addressing inefficiencies in construction processes [22,23]. Research highlighted how machine learning algorithms is applied in construction which can include optimisation of different tasks such as scheduling [24,25]. Concurrently, the rise of the Internet of Things (IoT) and cloud computing provided new avenues for real-time data collection and predictive analytics, further improving risk management and decision-making capabilities [26].

By the late 2010s, studies began to integrate AI with BIM to enhance its analytical capabilities [27,28]. Research demonstrated how machine learning models could predict project outcomes and automate routine design tasks, significantly reducing human error and improving project efficiency and risk prediction [29]. These advancements were complemented by the introduction of augmented reality (AR) and virtual reality (VR), which began to reshape how construction professionals visualised and interacted with project environments [7,30].

The early 2020s marked the advent of generative AI and large language models (LLMs), such as OpenAI's ChatGPT. These tools brought advanced natural language processing capabilities to many industries including the construction domain, enabling automated report generation, multilingual communication, and knowledge management [28,31,32]. Research has explored how generative AI could address inefficiencies in professional workflows and improve collaboration across diverse teams [33]. ChatGPT, in particular, gained attention for its ability to generate actionable insights from complex datasets, making it a valuable tool for decision-making in data-intensive projects [34–36].

The integration of generative AI into education and training began after 2021 [37]. Studies such as Uddin, Albert [10] showcased the application of ChatGPT as an educational resource for civil engineering students, where it fostered personalised learning and enhanced critical thinking. Researchers also began integrating generative AI with AR and VR platforms to create immersive training environments. For instance, Xu, Nguyen [30] demonstrated how these technologies provided real-time feedback and actionable guidance, significantly improving the quality and relevance of construction training programs.

From 2022 to 2024, research expanded to address the challenges of scaling generative AI in the construction industry [35,36,38]. Sh Said [39] highlighted the AI skill gap and discrepancies between academic curricula and the practical skills required in professional practice, emphasising the role of AI in bridging this gap [40]. Studies also explored the ethical implications and cybersecurity risks associated with AI adoption, proposing frameworks for responsible implementation [38]. Additionally, advanced use cases emerged, such as integrating ChatGPT with BIM, as well as real-time risk assessments and predictive maintenance [31,34].

By 2024, generative AI technologies were being used in sophisticated applications, including automated maintenance tasks, multilingual information retrieval, and dynamic safety assessments [32,41,42]. This chronological overview illustrates the progression from foundational BIM research to the current applications of generative AI and LLMs in construction. Early studies focused on digitising workflows and automating tasks, while more recent research emphasises AI-driven decision-making, immersive training, and ethical considerations. However, challenges such as scalability, skill alignment, and cybersecurity persist, requiring ongoing research and collaboration to maximise the benefits of these innovations.

3. Literature Review

This section critically evaluates the applications, benefits, and limitations of Generative AI and large language models (LLMs) such as OpenAI's ChatGPT, drawing from an extensive body of academic literature.

3.1. Generative AI in Construction Education

The integration of generative AI into construction education has enabled personalised, adaptive learning environments. Uddin, Albert [10] demonstrated ChatGPT's ability to foster critical thinking among civil engineering students by generating tailored educational materials and providing real-time feedback. Xu, Nguyen [30] expanded this by integrating ChatGPT with augmented reality (AR) systems to create immersive learning experiences, enabling students to practice safety protocols and project management strategies in simulated environments.

Historically, educational frameworks in construction have struggled to align with industry needs. Pulkkinen [43] and Sh Said [39] identified a significant gap between theoretical instruction and practical application. Generative AI addresses this gap by contextualising theoretical knowledge within real-world scenarios, offering students the opportunity to explore dynamic problem-solving approaches. Despite these advancements, challenges persist. Ghimire, Kim [44] noted that generative AI often lacks the capacity to impart hands-on skills. This emphasises the need for hybrid learning models that blend AI-driven theoretical education with practical fieldwork. Hoke [45] further cautioned against over-reliance on AI, highlighting the potential for diminished critical thinking skills if tools like ChatGPT are not used judiciously.

3.2. Generative AI in Construction Training

Generative AI has been transformative in developing dynamic training modules tailored to the specific needs of construction projects [42]. Uddin, Albert [46] examined how ChatGPT-enabled systems identified safety hazards and generated customised training content, significantly improving worker preparedness. Vision-language models integrated with ChatGPT have enhanced training by providing real-time visual instructions for complex tasks, as demonstrated by [4,8].

AR-enhanced training systems have further elevated generative AI's role in workforce development [22,30]. AR systems have enabled text-to-action functionalities, allowing trainees to receive actionable guidance directly in their field of view [47]. These systems have proven particularly effective in high-stakes environments, where precision is critical, and errors can result in significant human and financial costs. Historically, training in the construction industry has relied heavily on manual methods, which are often time-consuming and resource-intensive. Generative AI addresses these limitations by automating routine elements of training while providing tailored learning paths for individual workers [7,46]. Studies by Pulkkinen [43] underscore the importance of integrating AI with experiential learning to ensure comprehensive skill development.

3.3. Generative AI in Professional Practice

In professional construction workflows, generative AI has demonstrated its potential to enhance productivity and decision-making. ChatGPT has been employed to streamline documentation, automate compliance checks, and generate insights from large datasets [4,30,43,48]. These capabilities are particularly valuable in managing large-scale projects where data complexity can impede timely decision-making [6,44].

BIM systems integrated with ChatGPT have further expanded the utility of generative AI [27,31]. Research has highlighted the role of Generative AI and ChatGPT in optimising resource allocation, predicts scheduling conflicts, and enhances collaborative decision-making [49,50]. Multilingual capabilities have facilitated global collaborations, addressing communication barriers in diverse project teams [7,32]. Advanced applications, such as predictive maintenance and risk assessment, also showcase generative AI's versatility [29,34]. Rane [51] mentioned how ChatGPT analyses sensor data to anticipate equipment failures, enabling proactive maintenance and reducing downtime. Similarly, Uhm, Kim [42] explored its role in automating safety assessments, where generative AI evaluates on-site conditions to recommend preventive measures.

Table 1 provides a comparative analysis of the roles and applications of Generative AI, Large Language Models (LLMs), and ChatGPT across three core domains in construction: education, training, and professional practice. The table synthesises insights from the literature to highlight how these technologies are transforming the construction industry while identifying challenges that must be addressed to maximise their potential.

Table 1. Generative AI, Large Language Models (LLMs), and ChatGPT applications in construction: education, training, and practice.

Aspect	Construction Education	Construction Training	Construction Practice
Focus	Knowledge acquisition and theoretical understanding	Skill development and practical application	Optimisation of workflows and decision-making
Key Technologies	Generative AI, ChatGPT, Augmented Reality (AR), Virtual Reality (VR)	Generative AI, ChatGPT, AR, Vision-Language Models	ChatGPT, BIM integration, Domain-Specific LLMs
Applications of Generative AI, LLMs, and ChatGPT	Automated generation of educational content, personalised learning pathways, real-time question answering	Dynamic training content generation, real-time feedback for tasks, safety hazard identification	Automation of compliance checks, multilingual team collaboration, predictive maintenance
Major Benefits	Personalised learning, real-time feedback, enhanced engagement, bridging knowledge gaps	Real-time task guidance, improved safety protocols, task accuracy, immersive learning	Enhanced collaboration, multilingual capabilities, streamlined compliance, predictive maintenance
Challenges	Alignment with industry needs, lack of practical training, potential for over-reliance on AI	Scalability, ethical concerns, diverse site adaptation	Ethical concerns, data privacy, system interoperability
Example Applications	Personalised learning using ChatGPT; AR-based simulation of construction sites for safety training	AI-driven safety hazard recognition; AR-assisted step-by-step on-site training	AI-driven predictive maintenance; risk management planning with ChatGPT
References	[8,10,11,36,40,45,46,51–54]	[7,8,32,42,44,55]	[3,4,6,8,9,24,27,30,33,34,38,41–43,48,50,56]

In construction education, these technologies automate the generation of personalised learning materials, support real-time question answering, and enhance engagement through immersive technologies like Augmented Reality (AR) and Virtual Reality (VR) [30,36]. These innovations address long-standing challenges in aligning theoretical curricula with industry needs [40,45]. For construction training, generative AI delivers dynamic and context-sensitive training modules. ChatGPT's integration with AR platforms facilitates real-time, on-site task guidance and safety hazard identification, significantly improving task accuracy and safety protocols [7,46]. In construction practice, ChatGPT and domain-specific LLMs optimise workflows through automation of compliance checks, multilingual collaboration, and predictive maintenance [30,35,48]. These tools enhance collaboration, streamline decision-making, and support risk management in complex projects [5,9,34]. However, concerns such as ethical implications, data privacy, interoperability, and challenges in scalability and adapting to diverse environments remain significant barriers [32].

Table 2 presents a comprehensive comparison of Generative AI, Large Language Models (LLMs), and ChatGPT, specifically focusing on their applications, strengths, and limitations within the construction sector. It provides a detailed overview, starting with definitions to establish clarity about each concept and tool. Generative AI is characterised by its ability to create new content, such as safety manuals and project recommendations, and is highlighted for its versatility in predictive analytics and hazard prevention within the construction sector [3,9,33]. LLMs, on the other hand, focus on processing and generating natural language, making them instrumental in multilingual collaboration, technical report generation, and contract analysis [5,24,55]. ChatGPT, a tool built on LLMs, specialises in interactive applications, excelling in tasks such as personalised learning, immersive training, and real-time stakeholder communication [37,38,50].

Table 2. Comparison of Generative AI, Large Language Models (LLMs), and ChatGPT in construction sector.

Aspect	Generative AI	Large Language Models (LLMs)	ChatGPT
Definition	A subset of AI focused on creating new content, such as text, images, and models, based on input data.	Advanced AI models trained on vast text datasets to understand and generate human-like language.	A conversational AI model built on LLMs, designed for dialogue-based interactions.
Core Features	Content creation, predictive capabilities, and data synthesis across multiple formats.	Natural language processing, context understanding, multilingual capabilities.	Interactive text generation, real-time response, and task-specific customisation.
Applications in Construction	Automated content generation (e.g., safety manuals, design recommendations), predictive analytics for project planning, simulation of construction site scenarios, real-time data processing for risk assessment, automated compliance reporting, and proactive hazard prevention strategies.	Multilingual communication in global construction projects, generation of technical reports, analysis of legal documents and contracts, summarising project updates, real-time question-answering during meetings, integration with BIM for enhanced data insights, and predictive safety analytics.	Personalised learning pathways for construction education, AR-based immersive safety training, automated compliance checks, real-time safety hazard identification, collaborative document editing, support for multilingual project teams, generation of construction site daily logs, real-time safety guidance, and advanced risk management planning.
Strengths	Highly adaptable, versatile across applications, fosters innovation.	Highly accurate language comprehension; supports multilingual collaboration.	User-friendly interface, adaptable for diverse construction-related tasks, scalable across applications.
Limitations	Requires substantial computational resources, ethical concerns such as data misuse.	Can generate inaccurate content (hallucination), requires domain-specific tuning.	Prone to errors in complex queries, limited domain-specific depth without fine-tuning.
Key References	[3,4,6,9,27,28,31,33,40,41,43,44,48]	[5,9,24,25,32,42,52,55–58]	[4,10,30,31,34–38,46,50,51,54,59]

Table 2 underscores the unique contributions of each technology to construction education, training, and practice. Generative AI's strength lies in its adaptability across various applications, fostering innovation in project planning and compliance automation. LLMs are celebrated for their high accuracy in language comprehension and their ability to facilitate seamless communication across culturally diverse teams. ChatGPT's user-friendly interface and task-specific customisation make it particularly valuable for practical, on-the-ground applications, such as safety guidance and dynamic team coordination. Despite their significant contributions, these advancements and tools face notable challenges. Generative AI demands substantial computational resources and raises ethical concerns, while LLMs require fine-tuning for domain-specific applications to mitigate risks such as content hallucination. ChatGPT, while scalable and versatile, may produce errors in complex queries and relies heavily on proper configuration for optimal performance.

4. Methodology

This research employs a multi-stage methodology that is necessitated by its philosophical foundations required, recognising its complex, contemporary, and evolving nature [13,60]. The study adopts a pragmatic and exploratory methodological philosophy, aligning with the needs of investigating contemporary and evolving phenomena such as Generative AI and LLMs [61]. This philosophy emphasises flexibility, rigorous documentation, and the triangulation of findings to ensure validity and actionable outcomes. To address the inherent complexity and interdisciplinary demands of the study objectives, a multi-stage approach is essential [62]. Each stage builds on the preceding one, integrating theoretical exploration, empirical case studies, and comparative analysis to systematically address the research objectives [53]. The full research methodology process including the case study framework is shown in Figure 1.

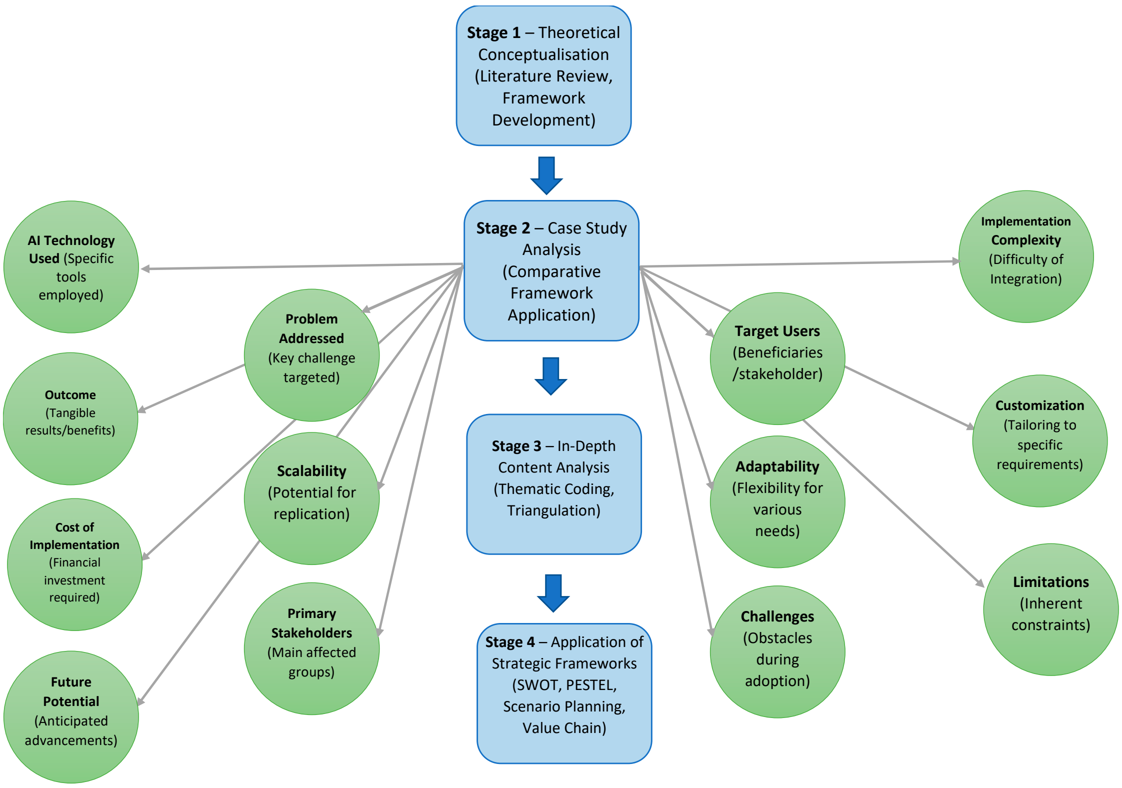

Figure 1. Research methodology process and case study framework.

4.1. Stage One Theoretical Conceptualisation

The initial stage of the methodology involved investigating the theoretical underpinnings of Generative AI, LLMs, and ChatGPT applications in the construction sector through an extensive review of relevant literature. This phase was exploratory and aimed to identify classifications and potential attributes of educational and training methodologies as well as professional practice tools [63,64]. The literature review focused on the following:

- The roles and applications of Generative AI, Large Language Models (LLMs), and ChatGPT in construction sector education, training, and professional practice.
- A comprehensive comparison of Generative AI, Large Language Models (LLMs), and ChatGPT, specifically focusing on their applications, strengths, and limitations within the construction sector.

This theoretical foundation guided the development of the case study framework, focusing on educational, workforce training, and professional applications, which is illustrated in Figure 1. The findings were validated by triangulating insights from various high-quality sources, ensuring their relevance and accuracy [65,66].

4.2. Stage Two Case Study Analysis

Case studies form a critical component of this research, offering in-depth insights into the real-world applications of Generative AI and LLMs. This study adopts an exploratory and comparative case study approach, inspired by methodologies suited for investigating innovative and evolving technologies in unstructured knowledge areas [53,67]. Document reviews and publicly available information were the primary sources of data. These included project documentation, industry reports, and academic articles [68]. Where necessary, participation consent was sought to access additional project-specific details, ensuring comprehensive data coverage [60,66]. The approach ensures comprehensive understanding, robust validation, and meaningful generalisation of findings. The key steps in this stage include the following:

1. Selection Criteria: Case studies were purposively selected to provide complementary information on AI's application in construction education, training, and practice [53,65]. Criteria included the presence of AI or digital tools, relevance to the research objectives, and availability of publicly accessible information. The selected cases encompass diverse contexts and sectors, capturing the complex nature of construction and infrastructure projects [26,69].
2. Framework for Comparative Case Study Analysis: The case comparisons were performed using a structured framework [70,71]. This framework was carefully designed to facilitate a methodologically sound assessment of AI applications by incorporating established evaluation criteria from prior studies that have investigated emerging and evolving digital technologies in complex and unstructured knowledge domains [26,60,67]. The study employs an exploratory and comparative case study approach, which is particularly suitable for examining innovative technologies where well-defined theoretical models may not yet exist [53]. The comparative case study framework in this study includes a multi-dimensional assessment model that evaluates AI applications based on technological, operational, economic, and strategic factors. The following components were established as fundamental criteria for evaluating the case studies:
    - AI Technology Used: The specific AI tools or technologies employed in each case.
    - Problem Addressed: The primary issue or challenge that the AI application aims to solve.
    - Target Users: The intended beneficiaries or stakeholders using the technology.

- Implementation Complexity: The level of difficulty in integrating the technology into workflows or processes.
- Outcome: The tangible results or benefits achieved through AI integration.
- Scalability: The potential to replicate or expand the solution across different contexts or projects.
- Adaptability: The flexibility of the AI application to suit various user needs or scenarios.
- Customisation: The ability to tailor the AI tool to specific project or organisational requirements.
- Cost of Implementation: The financial investment required for adopting the technology.
- Primary Stakeholders: The main groups or individuals involved in or affected by the AI deployment.
- Challenges: The obstacles encountered during the adoption or usage of the AI solution.
- Limitations: The inherent constraints or shortcomings of the technology in each context.
- Future Potential: The anticipated opportunities or advancements that the AI application could unlock.

By applying this comparative framework consistently across all cases, the analysis identified patterns, unique applications, strengths, weaknesses, and opportunities associated with the use of AI technologies in the construction sector. This structured approach ensured that each case study was evaluated comprehensively, providing actionable insights for industry stakeholders.

4.3. Stage Three In-Depth Content Analysis

The in-depth content analysis formed the foundation for synthesising data and deriving meaningful insights from the diverse applications of Generative AI, Large Language Models (LLMs), and ChatGPT in construction education, training, and professional practice. To ensure rigour, reliability, and academic validity, this study employed multiple qualitative research techniques, integrating content analysis, replication logic, triangulation of findings, thematic coding, and critical evaluation [72]. The analysis captured the nuanced and diverse applications of Generative AI in construction education, training, and practice. These methodological steps were designed to enhance the credibility, consistency, and generalisability of the research findings while maintaining alignment with best practices in qualitative construction management research.

Content Analysis: a widely used qualitative research technique was employed to structure and interpret data systematically. Each case study was examined through a comparative analytical framework that assessed AI applications based on key dimensions, including technology type, implementation context, scalability, adaptability, barriers, enablers, and measurable outcomes [53,66].

This structured approach ensured that insights from diverse construction domains—education, training, and professional practice—could be systematically compared and analysed. To further refine the study's insights, thematic coding was applied to classify findings under common categories such as AI-enhanced learning, workforce training efficiency, project risk assessment, and workflow automation. The analysis captured the nuanced ways in which AI technologies were integrated into construction workflows, highlighting the opportunities and constraints associated with their adoption. By systematically coding and categorising the data, the study was able to identify recurring trends, knowledge gaps, and sector-specific AI applications across various construction subfields [72,73].

Replication Logic: To enhance the validity and reliability of findings, replication logic was applied, ensuring that conclusions drawn from one case study could be corroborated or refined through comparisons with others [74].

This approach allowed the research to distinguish between generalised AI adoption patterns applicable across different domains and context-specific applications unique to individual case studies. For instance, while AI-enhanced construction education often focused on adaptive learning and real-time feedback, AI applications in professional practice were more geared towards workflow optimisation, compliance monitoring, and predictive maintenance. By systematically comparing these variations, the study was able to establish patterns that were both scalable and adaptable across different construction settings [75]. This iterative process strengthened the generalisability of the results and contributed to a robust analytical foundation [65,68].

Triangulation of Findings: Triangulation is a critical methodological tool in qualitative research, enabling the validation of findings through multiple sources and analytical perspectives. This study employed a three-pronged triangulation approach to enhance the credibility and depth of its insights [14,65]. Firstly, data triangulation was conducted by cross-referencing insights from case studies, industry reports, and academic literature to ensure consistency in the identified themes. Secondly, methodological triangulation involved the integration of different analytical techniques, such as thematic analysis, comparative case study evaluation, and replication logic, to validate AI adoption trends in construction. Finally, theoretical triangulation was applied to align research findings with existing frameworks in construction management, educational technology, and AI adoption models. This multi-layered validation strategy provided a holistic perspective on the role of AI in construction, allowing for greater analytical depth and empirical rigor [61].

Data Identification and Organisation: The initial step involved identifying relevant documents and ensuring their alignment with the research objectives [64]. Collected documents were systematically organised into themes according to the case study framework components discussed in the previous section (Figure 1). This categorisation provided a structured basis for further analysis and ensured that the data remained relevant and focused [72].

Thematic Coding: A six-step thematic coding process was applied to systematically classify and interpret key patterns within the data [13,53,64]. This involved the following:

- Initial Coding: Identifying recurring keywords and AI applications across case studies.
- Iterative Refinement: Refining the coding categories to enhance thematic clarity.
- Pattern Identification: Mapping AI adoption trends within construction education, training, and practice.
- Cross-Validation: Comparing themes across different case study contexts to assess consistency and variability.
- Domain-Specific Interpretation: Analysing unique AI applications relevant to each construction sub-sector.
- Final Classification: Organising the results into structured categories for systematic presentation and discussion.

This process enabled the study to extract meaningful insights while ensuring analytical coherence and methodological robustness. By applying rigorous thematic analysis, findings were not only systematically identified but also empirically validated, enhancing their academic credibility [61].

Critical Evaluation: Each document underwent critical evaluation to assess its reliability and relevance. This step was essential to ensure that the insights derived from the data accurately represented the context and objectives of the study [65].

Synthesis of Findings: A cohesive narrative was developed by integrating insights across multiple sources [65,73]. This synthesis highlighted trends, challenges, and opportunities, providing a foundation for the applications of strategic frameworks and analysis for Generative AI, LLMs, and ChatGPT in the construction domain [14].

4.4. Stage Four Application of Strategic Frameworks

The application of strategic frameworks represents a critical stage in the methodology, synthesising insights from theoretical conceptualisation and case study analysis. This stage integrates well-established analytical tools to evaluate and interpret the implications of Generative AI, LLMs, and ChatGPT in construction education, training, practice [6,76–82]. Each framework was selected based on its ability to provide a unique analytical perspective, complementing the findings of earlier stages and ensuring a comprehensive evaluation.

The rationale for incorporating strategic frameworks lies in their ability to systematically address multifaceted challenges and opportunities associated with technology integration [83]. Each framework contributes to different dimensions of analysis:

1. SWOT Analysis: Rooted in strategic management theory [6]; the SWOT framework has been utilised in different construction management studies [11,84–86]. The framework allows for the systematic identification of internal and external factors influencing AI and ICT integration. By categorising strengths, weaknesses, opportunities, and threats, SWOT analysis provides actionable insights into optimising AI adoption strategies [76].
2. PESTEL Analysis: A well-established tool for macro-environmental analysis which is a strong multidimensional, multilevel, sociotechnical conceptual framework [78,79], PESTEL evaluates the political, economic, social, technological, environmental, and legal contexts. This framework contextualises findings within broader industry and societal trends, aiding stakeholders making decisions and navigating external influences on AI implementation similar to previous research in the field [15,87,88].
3. Scenario Planning: Based on methodologies by Schoemaker [82], scenario planning explores potential future trajectories, considering socio-economic and technological uncertainties. This framework anticipates challenges and adapts strategies to align with dynamic industry conditions [81,89,90].

5. Results and Findings

The theoretical conceptualisation stage has led to the development of a mind map (Figure 2), which synthesises insights from an extensive review of the literature on the applications of Generative AI, Large Language Models (LLMs), and ChatGPT in the construction sector. This stage is integral to establishing a robust theoretical foundation, aligning with academic frameworks that prioritise conceptual clarity and systematic representation [53,61]. The mind map amalgamates diverse themes, technologies, applications, benefits, and challenges identified in the reviewed literature, presenting them in a hierarchical and visually structured format. It not only reflects the breadth of AI's transformative potential but also facilitates a nuanced understanding of its role in construction education, training, and practice. The mind map is based on an extensive literature review phase including information and concepts classified in Tables 1 and 2. At the centre of the mind map is the node Applications of Generative AI, LLMs, and ChatGPT in Construction, which serves as the focal point. This central node encapsulates the overarching theme derived from the literature, symbolising the unifying element of AI's application across the three primary domains: Construction Education, Construction Training, and Construction Practice. The central node is visually distinguished using a gold colour, representing its critical role as the foundation from which all thematic clusters radiate. This centrality aligns with established conceptual frameworks in academic research, where core constructs anchor the exploration of interrelated phenomena [17].

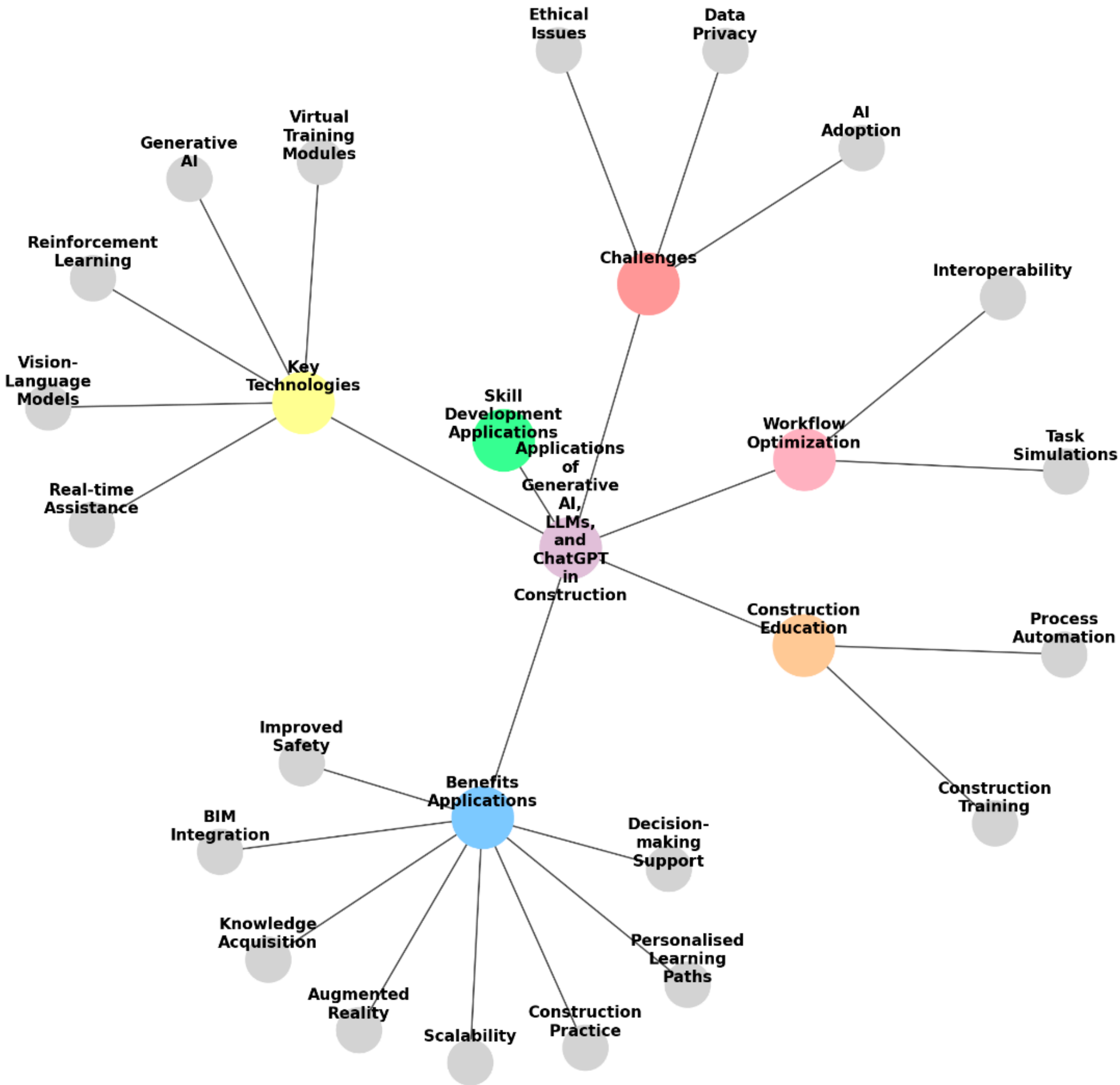

Figure 2. Mind map capturing the theoretical conceptualisation stage.

The colour coding within the mind map serves as a methodological tool to enhance clarity and conceptual differentiation. Each primary domain is assigned a distinct colour: light blue for education, light green for training, and light pink for practice. These choices reflect the thematic focus of each domain, aiding in the visual organisation and cognitive accessibility of the map. Detailed nodes under sub-branches are represented in light grey, maintaining neutrality while emphasising the granular insights derived from the literature.

The domain of Construction Education, depicted in light blue, explores the integration of AI in enhancing pedagogical methods and educational content delivery. Sub-branches within this domain, such as Knowledge Acquisition, Key Technologies, Applications, Benefits, and Challenges, reflect themes consistently highlighted in the literature [10,54].

For instance, technologies like Generative AI and augmented reality are identified for their ability to create interactive and personalised learning environments [55]. Applications such as automated content generation and customised learning paths exemplify practical implementations, aligning with pedagogical theories that emphasise adaptive and student-centred learning [4,24,36,52,57,91]. The literature also underscores challenges, including the misalignment between educational offerings and industry needs, necessitating strategic reforms to bridge this gap.

The Construction Training domain, represented in light green, highlights AI's potential to revolutionise skill development for instance in safety management and training [8,42,55]. Sub-branches like Skill Development and Applications showcase the use of AI tools, including virtual training modules and real-time task guidance systems, which enhance workforce preparedness and adaptability [7]. Technologies such as ChatGPT and vision-language models enable dynamic training environments, offering benefits such as increased safety and on-the-job learning opportunities [10,35,36,54]. However, the literature identifies challenges such as scalability and ethical concerns, particularly in maintaining equitable access to advanced training tools and addressing potential biases in AI systems. These findings align with workforce development theories, which advocate for integrating innovative tools to meet evolving industry demands.

The domain of Construction Practice, illustrated in light pink, delves into the practical implementation of AI in optimising workflows and enhancing collaboration. Sub-branches include Workflow Optimisation, Key Technologies, Applications, Benefits, and Challenges, reflecting the intricate balance between technological opportunities and operational constraints [30,34,48,58]. The literature highlights technologies like BIM integration and process automation for their role in streamlining project management and decision-making processes [27,28,31]. Applications such as multilingual communication tools and data-driven project optimisation are juxtaposed with challenges, including data privacy concerns and interoperability issues [9,32,36,38]. These insights resonate with theories of organisational innovation, which stress the importance of aligning technological advancements with strategic goals [14].

The rigorous and systematic approach adopted in development of the mind map illustrated in Figure 2 aligns with established academic practices, ensuring the framework's relevance, reliability, and applicability in advancing Construction 4.0 research and practice.

5.1. Case Study Results

The case studies were chosen based on a rigorous selection framework informed by theoretical conceptualisation and the availability of publicly accessible data as discussed in the methodology section. Key criteria included the relevance of AI applications to the domains of education, training, and practice, the presence of demonstrable outcomes, and diversity in technological adoption. The selected cases capture a wide range of contexts, from academic environments to on-site construction projects, ensuring a holistic understanding of AI integration. Data sources comprised project documentation, industry reports, and academic literature. A total of nineteen case studies were identified; accordingly, brief descriptions of all the cases are included in this section.

5.1.1. Construction Education (Seven Case Studies)

Case 1—Impact of ChatGPT on Student Writing in Construction Management: This case study focuses on the integration of ChatGPT into academic writing activities for construction management students, conducted at East Carolina University, United States. The initiative aimed to explore how generative AI tools like ChatGPT can be effectively used to enhance students' technical and professional writing skills, a critical component of construction education [59].

Case 2—Generative AI in Curriculum Development, USA: Western Michigan University in Michigan, USA implemented an AI-driven platform integrating generative AI and BIM into construction education. It features adaptive tools generating scenario-based learning, ChatGPT for personalised feedback, and web-based interactive modules. Students practice digital modelling, workflow optimisation, and automation skills through customised exercises, enabling hands-on learning and addressing key educational challenges in preparing for industry-specific roles [92].

Case 3—ChatGPT for Hazard Recognition—University Course, USA: In a construction program at a USA university, ChatGPT was used to simulate workplace hazards. Students interacted with the AI to identify risks, propose mitigation strategies, and discuss the implications of safety violations. The AI provided instant feedback on their responses, enhancing their ability to think critically about safety protocols [46].

Case 4—Developing Capstone Courses with Generative AI, USA: The case study from Texas A&M University explores using ChatGPT to design and refine the Capstone Project course in the Master of Engineering Technical Management (METM) programme. ChatGPT was employed to create grading rubrics, study plans, and learning activities, with human input refining the outputs. The study highlighted GPT-4Vs potential in enhancing instructional design while emphasising the necessity of human oversight [93].

Case 5—Enhancing Critical Thinking in Construction Management, Ecuador: Conducted at Universidad San Francisco de Quito, Ecuador; investigated how ChatGPT could aid civil engineering students in developing critical thinking skills. Students used GPT-4V to summarise and analyse video content on Lean Construction, generating questions to deepen their understanding. This activity aimed to promote analytical thinking, synthesis of information, and the ability to evaluate data critically [94].

Case 6—Integrating ChatGPT into Construction Surveying and Geomatics Education, USA: At a large USAstate university, ChatGPT was introduced as a learning tool in a civil engineering course focused on Construction Surveying and Geomatics. Students used ChatGPT to understand complex topics, ask follow-up questions, and generate concise, structured responses to foundational questions. The AI tool facilitated personalised learning by adapting to individual queries and providing detailed explanations in a conversational format. Its features, such as quick accessibility, ease of use, and the ability to summarise and clarify information, made it an effective supplementary resource for education in construction engineering [10].

Case 7—Using Generative AI in Construction Education, Germany: At Karlsruhe Institute of Technology (KIT), Germany; generative AI, including ChatGPT, was integrated into the Master of Science programme in Technology and Management in Construction. Students utilised AI for tasks such as Monte Carlo simulation scheduling, solar panel installation optimisation, and object detection from laser scans. The curriculum combined flipped classrooms, interactive sessions, and problem-based assignments to teach effective AI interaction and programming. GPT-V4 supported students in modularising problems, generating code, and simulating real-world projects like app development and robotic arm optimisation. It also fostered inclusivity by enabling multilingual interactions, preparing students for industry challenges with enhanced problem-solving and critical-thinking skills [40].

5.1.2. Construction Training (Five Case Studies)

Case 1—AI-Powered Safety Training Modules, Hong kong: viAct based in Hong Kongcreated AI-driven safety training modules that simulated real-world construction scenarios. Workers practiced identifying hazards, responding to emergencies, and adhering to safety protocols in a virtual environment. The generative AI created diverse training scenarios, allowing workers to face and solve various challenges [95].

Case 2—Maket's Generative AI in Construction Training, Canada: Maket, an AI-driven generative design platform, enhances training for construction professionals by integrating generative AI, including LLMs like ChatGPT, into design workflows. Maket leverages generative AI, including LLMs like ChatGPT, to enhance training for construction professionals by providing interactive tools for generating floor plans, exploring design styles, and optimising layouts. The platform offers real-time guidance on materials, costs, and regulations, enabling scenario-based learning and promoting sustainability through energy-efficient designs [96].

Case 3—Generative AI for Workflow Training by Stridely Solutions, India: Stridely Solutions developed generative AI modules to train construction workers in optimising workflows. These AI-driven tools simulate real-life scenarios using project data, allowing workers to enhance efficiency and adapt to changing conditions. The modules focus on design optimisation, workflow automation, and safety enhancements, providing a comprehensive virtual training experience. By preparing workers for real-world challenges in a risk-free environment, the program improves productivity and operational efficiency [97].

Case 4—AI Design Training for Construction Teams: The company implemented an AI design training program to educate its design team on using AI imaging tools. The training focused on accelerating design iterations, enabling the team to produce faster and more innovative solutions. By integrating AI into their workflows, the company aimed to improve efficiency, enhance creativity, and gain a competitive edge in the construction market [98].

Case 5—AI in Construction Training by RESTACK, Germany: RESTACK leverages AI to revolutionise construction workforce training by creating immersive virtual environments that replicate real-world site conditions. The platform offers personalised learning paths, real-time feedback, and scalable solutions to train large workforces efficiently. By automating administrative tasks and enhancing skill development, RESTACK improves employee engagement, safety, and operational efficiency in the construction industry [99].

5.1.3. Construction Practice (Seven Case Studies)

Case 1—Digs AI for Renovation Planning, USA: Digs developed an AI-powered progress tracking platform enabling homeowners and contractors to visualise renovation designs and manage logistics. The tool facilitated seamless communication between stakeholders, reducing errors and enhancing project coordination [100].

Case 2—Buildots' AI-Powered Progress Tracking, UK: Buildots employed wearable cameras equipped with AI to track construction progress and compare it to BIM data. The system automatically identified deviations from the plan and alerted project managers [101].

Case 3—Procore's AI-Enhanced Project Management, USA: Procore's AI features based in USA streamlined project management tasks, including document organisation, predictive analytics, and communication. The AI helped identify risks and suggest proactive measures [102].

Case 4—viAct's Real-Time Hazard Detection, Hong Kong: viAct applied AI to analyse site visuals and detect safety violations. The system provided real-time alerts, enabling immediate corrective actions and ensuring compliance with safety standards [101].

Case 5—Civils.ai for Document Search, UK: Civils.ai created an LLM-based tool for retrieving project-specific data from vast documentation. It covers construction AI workflows to analyse and run compliance checks on projects. The tool reduced the time spent searching for information and improved accuracy [103].

Case 6—STRABAG's AI and Generative Design for Construction, Astria: In partnership with Microsoft, STRABAG established a Data Science Hub and leveraged AI-driven solutions to optimise building design, mitigate risks, and improve operational efficiency. Generative design allows for the rapid creation and optimisation of multiple building designs, enabling more innovative and sustainable construction planning. AI risk assessment tools help minimise project risks and enhance decision-making [102].

Case 7—Skanska's AI Integration in Construction Processes, Sweden: Skanska utilises robotics and AI platforms to automate image capture, safety monitoring, and quality control on construction sites. The internal AI chatbot, Skanska Sidekick, supports content generation, information retrieval, and collaborative decision-making, streamlining communication and enhancing efficiency across projects [104].

5.2. Evaluation of Construction Education Case Studies

The analysis of construction education case studies demonstrates the profound impact of generative AI and large language models (LLMs), and mainly ChatGPT as the most widely known and utilised tool, on enhancing learning outcomes. Across the evaluated cases, a consistent focus emerges on equipping students with industry-relevant skills through interactive and adaptive learning technologies. For example, in the case of ChatGPT's integration at East Carolina University, students significantly improved their technical and professional writing skills, which are vital for the construction management domain. Similarly, the adoption of generative AI and BIM tools at Western Michigan University enabled hands-on learning in digital modelling, workflow optimisation, and automation, addressing key gaps in industry-specific education.

A notable trend is the use of AI to facilitate critical thinking and analytical skills. At Universidad San Francisco de Quito, ChatGPT enabled deeper engagement with Lean Construction concepts by encouraging students to synthesise information and develop questions, promoting a higher-order understanding of the material. Furthermore, the integration of ChatGPT into construction surveying and geomatics education highlighted the potential of AI to simplify complex topics and offer personalised, conversational learning experiences. However, these advancements are not without challenges. The cost of implementation in some cases and reliance on AI accuracy pose significant barriers, necessitating further refinement of these tools to ensure scalability and adaptability. Overall, these case studies underscore the transformative role of generative AI in construction education.

5.3. Evaluation of Construction Training Case Studies

The evaluation of construction training case studies highlights the potential of generative AI for advancing workforce development, particularly in safety training and workflow optimisation. For instance, viAct's AI-powered safety training modules provide virtual simulations of real-world scenarios, enabling workers to identify hazards, respond to emergencies, and adhere to safety protocols in a low-risk environment. Similarly, Maket's generative AI platform allows construction professionals to interact with tools for generating floor plans, exploring design styles, and optimising layouts, integrating sustainability into the training process.

Stridely Solutions' AI modules take this a step further by offering scenario-based training for workflow optimisation and safety enhancements, preparing workers for real-world challenges in a controlled, virtual environment. RESTACK's immersive virtual training solutions focus on operational efficiency, offering personalised learning paths and real-time feedback. Despite these successes, the implementation of AI in training faces notable challenges, including high costs and resistance to technology adoption. However, the scalability and adaptability of these solutions present immense potential for transforming workforce training. As demonstrated in these case studies, generative AI not only enhances skill acquisition but also prepares workers to adapt to dynamic industry conditions, setting a new standard for training effectiveness.

5.4. Evaluation of Construction Practice Case Studies

The exploration of AI applications in construction practice reveals significant advancements in operational efficiency, safety compliance, and design innovation. Case studies such as Buildots' AI-powered progress tracking illustrate how AI wearables streamline monitoring by identifying deviations from BIM models and providing real-time feedback to project managers. Similarly, STRABAG's use of generative AI for design optimisation and risk mitigation demonstrates the potential of AI to enhance sustainability and innovation in construction planning.

Procore's AI tools extend these capabilities by automating document management and predictive analytics, enabling better decision-making and risk mitigation. Meanwhile, viAct's real-time hazard detection showcases AI's ability to monitor safety compliance dynamically, reducing violations and improving worker safety. Despite these successes, challenges remain, including the complexity of integrating AI tools with existing systems and ensuring data accuracy. However, the scalability of these solutions and their adaptability to various project requirements highlight their potential to revolutionise construction practices. The case studies affirm that AI can significantly reduce inefficiencies, enhance safety standards, and foster innovation, offering a roadmap for broader industry adoption.

5.5. Comparative Case Study Analysis

The comparative analysis of construction education, training, and practice highlights distinct yet interconnected approaches to leveraging AI technologies, with differences observed across the themes of primary focus, key AI technologies used, major outcomes, target users, features, skills targeted, challenges, and future potential. These themes underscore how AI has been tailored to meet the unique needs of each domain while addressing broader industry demands.

Construction education is primarily centred on developing foundational skills, including technical writing, problem-solving, and critical thinking, to prepare students for industry roles (Table 3). For example, initiatives such as the integration of ChatGPT at East Carolina University enhanced students' professional writing capabilities, while Western Michigan University incorporates BIM tools and generative AI to facilitate hands-on digital modelling and workflow optimisation. In contrast, construction training focuses on workforce development, emphasising safety, operational efficiency, and workflow optimisation (Table 4). Programs such as RESTACK's immersive virtual environments and viAct's safety training modules provide practical, scenario-based exercises that enhance hazard recognition and operational skills. Construction practice addresses real-time project management, risk mitigation, and compliance monitoring, aiming to enhance operational workflows (Table 5). Tools like Buildots for progress tracking and STRABAG's generative design platforms exemplify how AI supports streamlined operations and innovation in construction workflows.

Table 3. AI technologies and tools used in construction education case studies.

Case Study	AI Technology Used	Problem Addressed	Target Users	Implementation Complexity	Outcome	Scalability	Adaptability	Customisation	Cost of Implementation	Primary Stakeholders	Challenges	Limitations	Future Potential
Impact of ChatGPT on Student Writing in Construction Management	ChatGPT	Improving technical and professional writing skills	Construction management students	Moderate	Enhanced student writing quality and learning outcomes	High	High	Moderate	Moderate	University faculty and students	Dependence on AI accuracy	Limited scope of AI responses	Integration with other teaching tools
Generative AI in Curriculum Development	ChatGPT, BIM tools	Hands-on learning for digital modelling, workflow optimisation	Construction students	High	Improved digital and automation skills	High	High	High	High	University faculty, industry advisors	Complex tool integration	Cost-intensive	Broader integration into curriculums
ChatGPT for Hazard Recognition-University Course	ChatGPT	Simulating workplace hazards for training	Construction students	Moderate	Improved safety awareness and critical thinking	High	High	Moderate	Moderate	University faculty and students	Need for advanced scenario creation	Limited adaptability	Integration into practical fieldwork
Developing Capstone Courses with Generative AI	ChatGPT	Enhancing capstone course design	Engineering students	Moderate	Improved instructional design and course materials	High	Moderate	High	Moderate	Faculty and programme administrators	Ensuring quality in AI outputs	Requires human oversight	Expansion to other engineering programs

Table 3. *Cont.*

Case Study	AI Technology Used	Problem Addressed	Target Users	Implementation Complexity	Outcome	Scalability	Adaptability	Customisation	Cost of Implementation	Primary Stakeholders	Challenges	Limitations	Future Potential
Enhancing Critical Thinking in Construction Management	ChatGPT	Developing analytical thinking and synthesis skills	Civil engineering students	Low	Improved understanding of Lean Construction concepts	High	High	Moderate	Low	Faculty and students	Ensuring active engagement	Limited critical thinking depth	Integration into project-based learning
Integrating ChatGPT into Construction Surveying	ChatGPT	Simplifying complex topics and offering interactive learning	Civil engineering students	Low	Personalised learning with enhanced conceptual understanding	High	High	Moderate	Low	Faculty and students	Over-reliance on AI	Limited scalability	Broader adoption in STEM education
Using Generative AI in Construction Education	ChatGPT, Generative AI tools	Advanced learning in real-world applications	Construction management students	High	Enhanced problem-solving and programming skills	High	High	High	High	Faculty and students	Resource-intensive implementation	High initial learning curve	Broader integration into university curriculums

Table 4. AI technologies and tools used in construction training case studies.

Case Study	AI Technology Used	Problem Addressed	Target Users	Implementation Complexity	Outcome	Scalability	Adaptability	Customisation	Cost of Implementation	Primary Stakeholders	Challenges	Limitations	Future Potential
AI-Powered Safety Training Modules	viAct	Simulating real-world safety scenarios	Construction workers	High	Improved hazard identification and response	High	High	High	High	viAct, construction firms	High implementation cost	Limited to safety scenarios	Broader adoption in site training
Maket's Generative AI in Construction Training	ChatGPT, Generative AI tools	Interactive training for workflow optimisation and sustainability	Construction professionals	High	Enhanced design efficiency and sustainability focus	High	High	High	High	Maket, industry professionals	High initial setup cost	Limited to specific applications	Expansion into other design training areas
Generative AI for Workflow Training	Stridely Solutions	Workflow optimisation and safety enhancement	Construction workers	Moderate	Improved productivity and operational efficiency	High	High	Moderate	Moderate	Stridely Solutions, construction firms	Limited real-world application	Needs high-quality data	Broader integration into workflow software
AI Design Training for Construction Teams	AI imaging tools	Accelerating design iterations and creativity	Construction design teams	High	Faster and more innovative design processes	High	High	Moderate	High	Design managers, industry professionals	Training on new tools	High learning curve	Expansion into advanced architectural design

Table 4. *Cont.*

Case Study	AI Technology Used	Problem Addressed	Target Users	Implementation Complexity	Outcome	Scalability	Adaptability	Customisation	Cost of Implementation	Primary Stakeholders	Challenges	Limitations	Future Potential
AI in Construction Training	RESTACK AI applications	Enhancing workforce training efficiency	Construction workers and managers	High	Improved engagement and safety	High	High	High	High	Workforce managers, construction firms	Resistance to technology adoption	Cost-intensive	Integration with AR and real-time applications

Table 5. AI technologies and tools used in construction practice case studies.

Case Study	AI Technology Used	Problem Addressed	Target Users	Implementation Complexity	Outcome	Scalability	Adaptability	Customisation	Cost of Implementation	Primary Stakeholders	Challenges	Limitations	Future Potential
Digs AI for Renovation Planning	AI-powered progress tracking	Streamlining renovation planning and logistics	Homeowners and contractors	Moderate	Improved project coordination and reduced errors	High	High	Moderate	Moderate	Digs, contractors	Ensuring user adoption	Limited to renovation projects	Integration into broader construction workflows

Table 5. *Cont.*

Case Study	AI Technology Used	Problem Addressed	Target Users	Implementation Complexity	Outcome	Scalability	Adaptability	Customisation	Cost of Implementation	Primary Stakeholders	Challenges	Limitations	Future Potential
Buildots' AI-Powered Progress Tracking	AI wearables	Progress tracking and deviation identification	Project managers	Moderate	Enhanced project monitoring and real-time feedback	High	High	Moderate	Moderate	Buildots, construction managers	Data accuracy issues	Limited scalability	Broader integration with BIM systems
Procore's AI-Enhanced Project Management	Procore AI	Streamlining document management and predictive analytics	Construction managers	Moderate	Improved project planning and risk mitigation	High	High	High	High	Procore, project managers	Ensuring data integration	Limited to Procore systems	Broader implementation in industry-wide platforms
viAct's Real-Time Hazard Detection	viAct AI	Analysing site visuals to detect safety violations	Construction site managers, workers	High	Reduced safety violations and improved compliance	High	High	High	High	viAct, construction firms	Dependence on visual data	Limited adaptability	Integration with wearable tech and robotics
Civils.ai for Document Search	Civils.ai LLM tool	Simplifying project-specific data retrieval from vast documentation	Construction professionals	Moderate	Reduced time in searching information and improved accuracy	High	High	Moderate	Moderate	Civils.ai, construction firms	Limited to text-based tasks	Dependence on document quality	Broader integration into compliance workflows

Table 5. *Cont.*

Case Study	AI Technology Used	Problem Addressed	Target Users	Implementation Complexity	Outcome	Scalability	Adaptability	Customisation	Cost of Implementation	Primary Stakeholders	Challenges	Limitations	Future Potential
STRABAG's AI and Generative Design for Construction	AI-driven design tools	Optimising building designs and risk mitigation	Design and construction teams	High	Enhanced innovation and operational efficiency	High	High	High	High	STRABAG, construction professionals	High initial implementation cost	Complexity in AI training	Expansion into real-time design optimisation

Each domain employs AI tools specific to its objectives. Construction education integrates generative AI tools such as ChatGPT with BIM platforms to foster interactive learning and digital modelling (Table 3). Training relies on immersive platforms like RESTACK, viAct, and other generative AI solutions for virtual simulations and sustainability-focused design (Table 4). Construction practice leverages tools like Buildots for progress tracking, Procore AI for document management, and STRABAG's generative design platforms for risk assessment and workflow optimisation (Table 5). These tailored tools reflect the distinct needs of each domain while highlighting AI's versatility.

The outcomes differ across domains, reflecting their unique objectives. Education results in improved technical writing, critical thinking, and automation skills among students, aligning with academic and industry expectations (Table 3). Training enhances workforce safety compliance, productivity, and sustainability awareness through immersive and scenario-based exercises (Table 4). Practice achieves streamlined operations, real-time monitoring, and innovation in design and construction workflows (Table 5). While education and training focus on skill acquisition, practice delivers measurable improvements in operational efficiency.

The target users in each domain vary, reflecting their distinct roles in the construction lifecycle. Construction education caters to students and faculty, aiming to align academic curricula with industry requirements (Table 3). Training targets construction workers, managers, and design teams who require upskilling for real-world applications (Table 4). Practice serves contractors, project managers, and construction teams, focusing on optimising daily operations and decision-making processes (Table 5). This diversity highlights AI's ability to address the needs of various stakeholders across the construction sector.

The AI features employed in each domain align with their respective objectives. Education benefits from adaptive feedback, scenario generation, and personalised learning tools that facilitate deeper engagement and understanding (Table 3). Training relies on immersive simulations, real-time feedback, and workflow automation to provide hands-on, practical learning experiences (Table 4). Practice incorporates real-time project tracking, risk assessment, and predictive analytics to streamline operations and enhance decision-making (Table 5). These features underscore AI's capacity to adapt to the complexity of tasks within each domain.

Construction education targets foundational skills such as technical writing, problem-solving, and critical thinking (Table 3). Training focuses on developing safety awareness, workflow optimisation, and operational efficiency, ensuring workers are prepared for industry challenges (Table 4). Practice enhances project management, compliance monitoring, and design innovation, equipping professionals with the skills needed for advanced construction operations (Table 5). Together, these domains provide a comprehensive skill set that supports the construction industry's evolving needs.

Despite their successes, each domain faces distinct challenges. Education struggles with resource-intensive implementation and reliance on AI accuracy (Table 3). Training encounters high costs and resistance to adopting new technologies among workers (Table 4). Practice deals with integration complexity, data accuracy, and high implementation expenses (Table 5). These challenges underscore the importance of addressing barriers to ensure the scalability and sustainability of AI solutions across all domains.

In addition, Table 6 provides a comparative analysis across these themes reveals the transformative role of AI in construction education, training, and practice. While each domain employs AI differently to meet its objectives, they collectively contribute to the construction industry's advancement by enhancing skills, improving safety, and optimising operations. A key disparity lies in the alignment of skills across domains. Education focuses heavily on theoretical knowledge, often leaving graduates underprepared for hands-on tasks highlighted in training and practice. Similarly, while training excels in site-based skill development, it lacks emphasis on higher-order strategic competencies central to practice. This disconnect highlights a need for integrated pathways that bridge foundational, practical, and advanced skill sets across the construction lifecycle. Challenges vary across domains but are interconnected. Education faces barriers such as resource-intensive implementation and dependency on AI accuracy. Training encounters resistance to technology adoption and high costs, particularly for immersive platforms. Practice grapples with integration complexity and data reliability, limiting the scalability of advanced AI applications. These shared challenges underline the importance of refining AI tools to improve accessibility, reliability, and usability.

Table 7 presents a comparative analysis of AI adoption across three domains: construction education, workforce training, and construction practice. The table identifies key success and failure factors associated with Generative AI, LLMs, and ChatGPT, and evaluates how these findings corroborate or challenge the existing literature. In construction education, the success factors highlight AI's role in enhancing adaptive learning, technical writing, and safety awareness. However, failure factors include over-reliance on AI reducing critical thinking, high implementation costs, and scalability constraints. These findings align with literature on AI-driven education but challenge claims that AI inherently improves independent problem-solving skills. For workforce training, AI has demonstrated success in improving safety awareness, workflow automation, and personalised upskilling. However, high costs, workforce resistance, and ethical concerns regarding job displacement remain significant barriers. This corroborates studies on AI-driven safety improvements but challenges overly optimistic assumptions about seamless AI integration into construction training. In construction practice, AI applications have been successful in compliance tracking, project monitoring, and generative design, contributing to efficiency, cost reduction, and sustainability. Nonetheless, the sector faces barriers related to legacy system integration, data accuracy issues, and high investment costs. These challenges contradict some literature that overstates AI's ease of adoption and reliability in construction workflows. This structured evaluation of AI adoption provides critical insights for industry stakeholders, policymakers, and researchers, ensuring a comprehensive understanding of AI's opportunities and limitations in the construction sector.

Table 6. Comparative table of findings across construction education, training, and practice.

Domain	Primary Focus	Key AI Technologies Used	Major Outcomes	Target Users	Features	Skills Targeted	Challenges	Future Potential
Construction Education	Enhancing technical skills, critical thinking, and AI integration in curricula	ChatGPT, BIM tools, Generative AI	Improved technical writing, safety awareness, problem-solving, and automation skills	Students, faculty	Adaptive feedback, interactive modules, scenario generation	Technical writing, critical thinking, problem-solving, AI literacy	Resource-intensive implementation, reliance on AI accuracy	Integration with industry needs, advanced curricula, and expanded accessibility
Construction Training	Workforce development, safety training, workflow optimisation	ChatGPT, RESTACK AI, Generative AI tools	Enhanced safety protocols, productivity, and workflow efficiency	Construction workers, managers	Virtual simulations, real-time feedback, workflow automation	Safety awareness, productivity, operational efficiency, design optimisation	High implementation costs, resistance to adoption	Integration with AR/VR, real-time applications, and industry-wide adoption
Construction Practice	Real-time project management, progress tracking, and safety monitoring	Procore AI, Buildots AI, viAct, Civils.ai, STRABAG AI	Enhanced project coordination, reduced errors, compliance, and innovation	Contractors, project managers	Real-time monitoring, automated tracking, risk analysis	Project management, risk mitigation, compliance, innovation	Complexity in tool integration, data accuracy issues	Expansion into predictive analytics, collaborative AI systems, and autonomous operations

Table 7. Success, failure and literature corroboration across construction education, training, and practice.

Case Study Domain	Critical Success Factors	Critical Failure Factors	Corroboration with Literature	Challenges to Literature
Construction Education	Adaptive AI learning models enhance engagement and personalised instruction; AI-supported technical writing improves comprehension and report accuracy; Scenario-based AI simulations improve safety awareness.	Over-reliance on AI reduces critical thinking and problem-solving; Resource-intensive implementation limits widespread adoption; AI-enhanced curricula have scalability constraints.	Aligns with studies on AI's role in personalised education and adaptive learning models; Confirms research on AI-driven knowledge retention in technical disciplines.	Contrasts with studies suggesting AI enhances critical thinking; Demonstrates financial and infrastructural constraints as key barriers to AI scalability, which is underexplored in existing literature.
Workforce Training	AI-driven safety monitoring and workflow automation significantly reduce errors; Personalised AI training enhances upskilling efficiency; Real-time AI analysis improves site hazard identification.	High costs of AI training tools limit SME adoption; Resistance among experienced workers to AI-driven methods; Ethical concerns regarding automation and job displacement.	Supports literature on AI's ability to improve safety awareness and efficiency in training; Reinforces studies on AI-driven real-time risk assessments.	Challenges optimistic views of seamless AI adoption by highlighting SME financial constraints and workforce resistance; Raises ethical concerns about AI's impact on employment not fully addressed in prior research.
Construction Practice	AI-enabled compliance tracking and project monitoring enhance efficiency; Generative AI reduces design costs and improves sustainability; AI-assisted documentation reduces regulatory risks.	Integration complexity with legacy systems hinders adoption; Data accuracy and reliability concerns in AI-driven decision-making; High financial investment required for implementation.	Validates research on AI-driven project monitoring efficiency; Confirms findings on AI-enhanced documentation improving compliance and risk reduction.	Contradicts claims of smooth AI integration by showcasing technical and organisational barriers; Raises concerns about AI reliability, contradicting literature emphasising AI's accuracy in decision-making.

6. Analysis of AI Applications in Construction: A Comprehensive Approach

This analysis of Generative AI, Large Language Models (LLMs), and ChatGPT in construction education, training, and practice integrates theoretical frameworks, empirical evidence, and case studies. It uses SWOT, PESTEL, Value Chain, and Scenario Planning to provide a multidimensional evaluation. Each framework is contextualised within the construction industry, supported by relevant academic literature, and cross-referenced with practical applications to offer an elaborate academic discussion.

6.1. SWOT Analysis

The results of the SWOT analysis are included in this section and illustrated by Figure 3. The strengths of AI are evident in its ability to automate processes, optimise workflows, and enhance decision-making. For example, tools like Buildots facilitate real-time progress tracking, reducing delays and increasing transparency [101]. Similarly, Civils.ai's document search functionality addresses inefficiencies in accessing project data, streamlining administrative tasks [103].

Customisation and adaptability further enhance AI's strengths. AI-powered training modules, such as those by Laing O'Rourke, can be tailored to meet specific learning objectives, improving workforce engagement and knowledge retention. However, weaknesses include the significant costs associated with implementing advanced AI technologies, such as VR simulations for equipment training, which require substantial infrastructure investment and technical expertise [7,30]. Data quality and availability are critical challenges, as incomplete or inaccurate datasets can compromise the performance of AI systems [8,23,36].

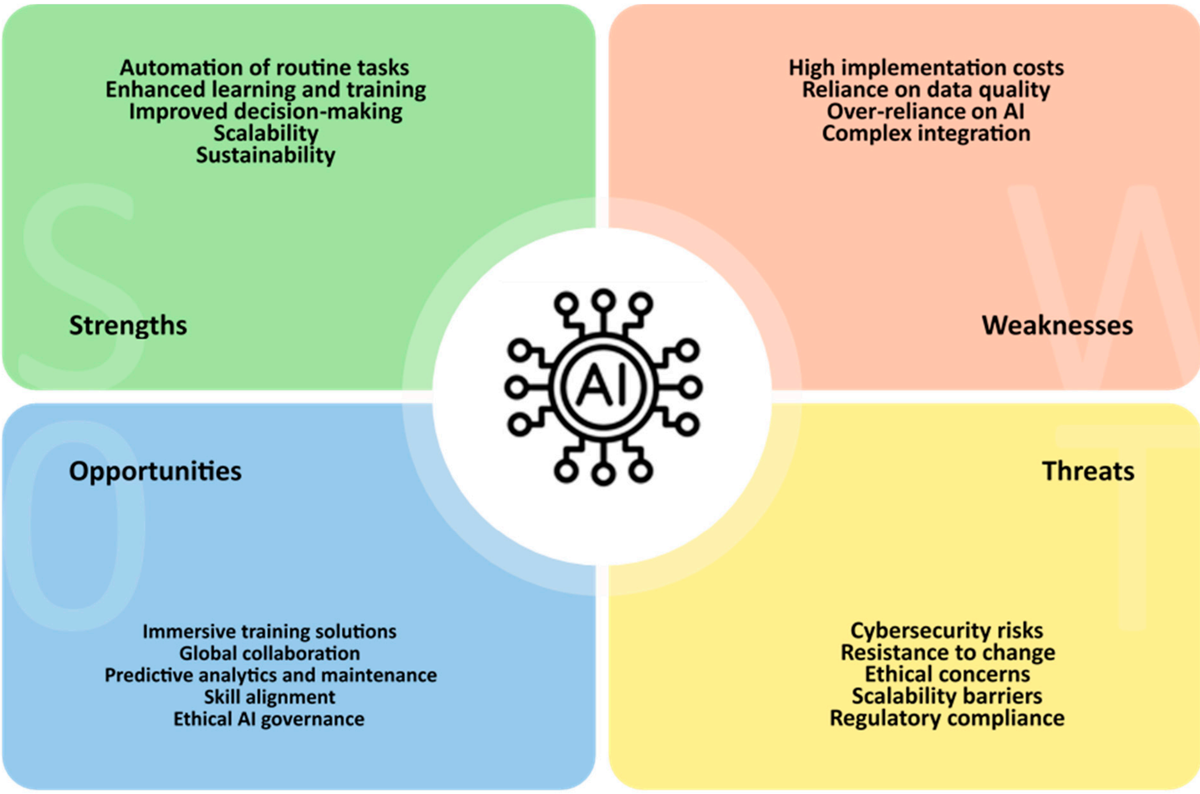

Figure 3. SWOT analysis of generative AI, large language models and ChatGPT adoption in construction.

Opportunities arise from AI's scalability and alignment with global trends in digital transformation. Scalable solutions, such as ChatGPT for technical support, can be deployed across diverse construction contexts, addressing a wide range of challenges. Environmental sustainability represents another key opportunity, with generative AI enabling resource-efficient designs and minimising waste [6,23,44]. Nevertheless, threats such as resistance to change and ethical concerns persist. The construction industry's slow adoption of new technologies reflects entrenched practices and cultural barriers [15]. Moreover, ethical issues related to data privacy and algorithmic bias demand robust governance frameworks to ensure equitable and responsible AI use [8,15,23,36].

6.2. PESTEL Analysis

Political Factors: Global policy initiatives supporting digital transformation and sustainability, such as the European Green Deal and the U.S. Infrastructure Investment and Jobs Act, and can be used to encourage the integration of Generative AI, LLMs, and ChatGPT into construction workflows. These policies align with smart cities and sustainable construction goals, promoting digital innovation and environmental responsibility [105,106]. However, strict regulations like the General Data Protection Regulation (GDPR) in Europe pose challenges to collecting and using large datasets essential for AI training and operation [107]. Balancing innovation with data privacy remains a critical political consideration, particularly as global policies, such as the UN's Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure), emphasise the need for resilient and inclusive infrastructure.

Economic Factors: The economic implications of AI adoption in construction present a dual challenge. While tools like ChatGPT are cost-effective and widely accessible, advanced systems such as predictive maintenance platforms and AI-integrated BIM tools demand significant initial investment [27,30,31]. For small and medium-sized enterprises (SMEs), these costs can be prohibitive, potentially exacerbating inequality in technological access. However, the long-term economic benefits are substantial, including reduced project delays, lower rework rates, and optimised resource utilisation, which align with SDG 8 (Decent Work and Economic Growth) by enhancing productivity and promoting innovation.

Social Factors: Generative AI and LLMs play a transformative role in addressing workforce skill gaps through personalised and scalable training solutions. AI-driven micro-learning modules and ChatGPT-supported learning provide workers with tailored educational content, improving competency and accessibility [10,36,45]. However, fears of job displacement due to automation highlight the need for transparent communication and robust reskilling programs. These efforts align with SDG 4 (Quality Education) by ensuring inclusive and equitable access to lifelong learning opportunities [108]. Promoting social acceptance of AI requires balancing its benefits with strategies that support human-centric job roles and ensure equitable technological integration.

Technological Factors: Advances in natural language processing, machine learning, and data analytics enable innovative applications of Generative AI and LLMs, such as real-time hazard detection, generative design, and multilingual communication. These advancements address critical inefficiencies in construction processes, improving decision-making and operational workflows [48,97]. However, integrating these technologies with legacy systems and achieving data interoperability remain significant hurdles [6]. Addressing these challenges will require establishing industry-wide standards and fostering collaborations between technology providers and construction firms, thus supporting SDG 9's focus on resilient infrastructure and technological innovation.

Environmental Factors: AI-driven tools contribute to sustainable construction by minimising material waste, optimising resource use, and promoting energy efficiency [5,48]. Applications such as BIM-enabled energy modelling and lifecycle analysis support green building initiatives, aligning with SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action) [18,19]. (Furthermore, AI-enhanced project management facilitates sustainable decision-making, reducing environmental impact throughout the project lifecycle.

Legal Factors: Evolving legal frameworks, including intellectual property rights, data protection regulations, and ethical guidelines for AI, shape the adoption of Generative AI and LLMs. Compliance with global standards, such as the GDPR and the AI Act in the European Union, ensures transparency and accountability in AI deployment [109,110]. Additionally, ethical considerations, such as bias mitigation and fairness, are integral to fostering trust in AI technologies. Legal and ethical alignment is essential for scalable and sustainable implementation, directly supporting SDG 16 (Peace, Justice, and Strong Institutions) by promoting inclusive and accountable practices in AI governance [108,111].

6.3. Scenario Planning Analysis

In a high-adoption scenario, AI integrates into all construction phases, driving efficiency, collaboration, and sustainability. Tools like generative design platforms and predictive analytics revolutionise design optimisation, construction monitoring, and maintenance forecasting. For instance, AI systems such as Maket and Autodesk enable rapid creation of optimised designs [96]. Safety systems like Safesite detect hazards in real-time, while AI chatbots like Skanska's Sidekick improve collaboration [104]. This scenario aligns with McKinsey's prediction that AI adoption will redefine competitiveness, though significant investment in infrastructure and training is essential [112].

In a moderate-adoption scenario, AI adoption advances incrementally due to resistance to change and financial barriers. Organisations focus on specific applications like safety compliance and training. Tools such as AI-powered training simulations from Restackio and robotic technologies like SAM enhance skills and efficiency [99]. However, the lack of a comprehensive AI strategy limits industry transformation. While some inefficiencies are addressed, incremental progress leaves organisations vulnerable to disruption by more ambitious global peers.

A low-adoption scenario sees the industry relying on traditional methods, missing opportunities for innovation. Without tools like GeoSpatial AI or Pix4D, organisations fail to optimise site selection or monitor projects effectively [102]. This stagnation risks rendering organisations uncompetitive as global competitors leverage AI to improve productivity, safety, and sustainability.

Rapid AI advancements could disrupt the industry with breakthroughs in generative AI, robotics, and machine learning. Autonomous systems might execute complex tasks with minimal human intervention, and platforms like Merit's data engine could streamline regulatory compliance. However, these advancements introduce ethical concerns like algorithmic bias and job displacement, requiring strategies to upskill the workforce and manage disruptions [15,99]. Regulatory frameworks must evolve to address these challenges.

7. Discussion

The manuscript provides a detailed exploration of generative AI and LLMs in the construction industry, presenting an in-depth analysis of their impacts on education, training, and practice, alongside scenario planning, SWOT, and PESTEL frameworks. The discussion synthesises these findings to evaluate the transformative potential of AI, the discrepancies between skill requirements across domains, and the implications of these gaps.

In education, AI-driven tools like ChatGPT and BIM integration enable students to develop foundational knowledge and critical thinking skills. Examples include curriculum enhancements through generative AI and project-based learning platforms that simulate real-world scenarios. These technologies foster theoretical understanding and analytical abilities. However, the findings reveal a gap in translating these educational outcomes into practical, job-ready skills. While students excel in conceptual learning, they often lack exposure to real-world complexities, such as decision-making under constraints and adaptive problem-solving. This misalignment necessitates hybrid models that blend AI-enabled academic learning with experiential, hands-on training.

In training, generative AI significantly enhances workforce readiness by delivering task-specific skill development. Tools like viAct's safety modules and RESTACK's immersive virtual environments equip workers with practical competencies in hazard recognition, equipment operation, and workflow optimisation. These technologies address immediate site-based requirements effectively, ensuring safety compliance and operational efficiency. However, the emphasis on site-specific tasks often neglects the strategic and higher-order skills essential for leadership roles. Training programmes need to incorporate broader competencies, such as resource management, collaboration, and strategic planning.

Practice demonstrates a demand for advanced operational and strategic skills, where AI tools like Buildots and STRABAG's generative systems optimise workflows, resource allocation, and decision-making. These applications require a blend of foundational knowledge and practical expertise, along with the ability to navigate complex, multidisciplinary projects. The PESTEL analysis reveals how technological advancements drive these applications while also exposing regulatory and interoperability challenges. The discrepancy between education, which focuses on theory, and training, which emphasises task-specific skills, often leaves professionals underprepared for the strategic demands of modern construction workflows.

As one of the more widely applied tools, The integration of ChatGPT into construction education, workforce training, and professional practice signifies a major shift in the way artificial intelligence (AI) is utilised to enhance learning, decision-making, and project execution. Findings from the case studies demonstrate that ChatGPT's capabilities extend beyond conventional text-based assistance to include adaptive learning models, real-time safety simulations, and AI-driven compliance monitoring. In construction education, ChatGPT has proven effective in facilitating interactive learning environments where students receive instant feedback, refine their technical writing skills, and engage in AI-assisted problem-solving exercises. For instance, its application in lean construction and geomatics education has enabled students to analyse construction workflows, conduct virtual assessments, and engage with AI-generated project scenarios that mimic real-world complexities. These applications align with literature advocating for AI-driven pedagogical models that enhance critical thinking, knowledge retention, and engagement. However, while ChatGPT's role in academic environments presents significant advantages, concerns remain regarding over-reliance on AI-generated outputs, potential biases in algorithmic responses, and the diminished development of independent analytical skills among students. Furthermore, the technical and financial barriers to large-scale adoption suggest that institutions require substantial infrastructural and pedagogical adjustments to optimise ChatGPT's integration into their curricula.

In the domain of workforce training and construction practice, ChatGPT has been successfully deployed in real-time safety monitoring, workflow automation, and multilingual communication, enhancing the efficiency and effectiveness of on-site decision-making and compliance tracking. Platforms such as STRABAG AI, Maket, and viAct demonstrate the efficacy of AI-driven hazard identification, risk assessment, and regulatory compliance enforcement, reinforcing findings from recent studies that emphasise the role of AI in reducing human errors and improving construction site safety protocols. Additionally, ChatGPT's language processing capabilities allow for seamless cross-border collaboration, particularly in multinational construction projects, by translating technical documentation and supporting real-time project communication across diverse linguistic backgrounds. Despite these advantages, several challenges persist, including concerns over AI's ability to interpret complex site-specific data, ethical considerations related to AI-driven automation replacing human expertise, and interoperability issues between AI-based and traditional construction management systems. These findings suggest that while ChatGPT and similar AI models have the potential to enhance productivity and knowledge dissemination, their integration into the construction sector must be strategically planned, continuously monitored, and aligned with regulatory and ethical frameworks. To achieve sustainable AI adoption, future research must focus on establishing best practices for AI-human collaboration, ensuring data security in AI-assisted decision-making, and developing robust evaluation metrics to assess ChatGPT's long-term impact on construction education and operations.

The matrix-style comparative Table 8 provides a structured cross-comparison of case studies within the SWOT, PESTEL, and Scenario Planning frameworks. It highlights the strengths and opportunities of AI integration, such as enhanced learning engagement, improved hazard recognition, and streamlined design workflows, while also acknowledging the challenges, including AI dependency, workforce resistance, and high implementation costs. By linking these findings to literature, the table demonstrates that while AI adoption aligns with ongoing research on efficiency gains and digital transformation, it also challenges optimistic assumptions about seamless integration and universal scalability. This format helps contextualise AI-driven innovations in construction education, training, and practice, offering a multidimensional evaluation that can inform strategic decision-making for academia and industry.

Table 8. Matrix-style comparative table linking SWOT, PESTEL, and scenario planning to specific case studies.

Case Study	SWOT (Strengths and Weaknesses)	PESTEL (External Factors)	Scenario Planning (Adoption Trajectory)	Link to Literature
ChatGPT in Student Writing	Strengths: AI-assisted learning enhances engagement and improves student writing; Weaknesses: Over-reliance on AI can reduce critical thinking and independent problem-solving.	Political: AI governance policies in education are still developing; Economic: High AI implementation costs limit accessibility; Technological: AI literacy varies among students and educators.	High-adoption scenario: AI becomes a standard writing and feedback tool in education; Low-adoption scenario: AI remains a niche tool, used only by select institutions.	Supports research on AI-enhanced education but raises concerns about student dependency on automated tools.
AI in Safety Training	Strengths: AI-driven safety training reduces site accidents and improves hazard recognition; Weaknesses: Resistance from experienced workers and lack of AI integration in standard safety protocols.	Political: Safety regulations slowly adapting to AI-driven models; Economic: Training cost is high, limiting SME adoption; Technological: AI-based safety training tools require integration with real-world environments.	High-adoption scenario: AI safety training is mandated in high-risk construction sites; Low-adoption scenario: Traditional methods continue, limiting AI's effectiveness.	Aligns with studies on AI-driven hazard mitigation but highlights adoption barriers due to training costs and resistance.
Maket's AI in Training	Strengths: Generative AI enhances design thinking and workflow optimisation in training; Weaknesses: High implementation costs and lack of familiarity among SMEs.	Political: Lack of AI training incentives for SMEs; Economic: High upfront costs deter adoption; Social: Resistance from experienced professionals who prefer traditional training methods.	High-adoption scenario: AI training platforms become mainstream, driven by digital transformation efforts; Low-adoption scenario: AI remains an experimental tool with limited industry adoption.	Corroborates literature on AI in training but points out economic constraints for SMEs adopting generative AI.
STRABAG's Generative AI	Strengths: AI-enabled design automation streamlines project planning and reduces design errors; Weaknesses: Compatibility issues with existing BIM systems and resistance from traditional designers.	Political: Construction regulatory bodies lag in AI adoption policies; Economic: High capital investment required for generative AI; Technological: Lack of seamless integration with traditional project workflows.	High-adoption scenario: AI-driven generative design becomes integral to major construction projects; Low-adoption scenario: Traditional BIM workflows persist, limiting AI's impact.	Supports findings on AI-powered design automation but identifies cost and training hurdles as key barriers to implementation.

The impact timeline presented in Table 9 illustrates a longitudinal perspective on AI adoption, outlining the short-term, medium-term, and long-term effects across different domains. In the immediate term (1–2 years), AI adoption shows incremental improvements in education (technical writing enhancement), training (hazard identification), and practice (workflow automation). Over the medium term (3–5 years), institutions and firms adapt AI-driven solutions more widely, refining curricula, training methodologies, and regulatory frameworks to accommodate AI technologies. In the long term (6+ years), AI is expected to become a standard tool for education, compliance, and project management, fundamentally reshaping how construction professionals learn, train, and operate. This timeline-based analysis provides a strategic roadmap for stakeholders to anticipate adoption trends, policy implications, and necessary skill developments for sustainable AI integration.

The adoption barrier and mitigation strategy are captured in Table 10 and focuses on the practical challenges of AI implementation and proposes structured solutions to overcome these obstacles. It identifies key barriers such as over-reliance on AI in education, resistance to AI-driven safety training, high costs of AI-based workforce training, and integration difficulties in construction workflows. The proposed mitigation strategies emphasise hybrid AI-human learning models, phased AI adoption strategies, government incentives for SMEs, and structured AI upskilling programs to support effective implementation. By directly linking barriers to solutions, this table provides actionable insights for policymakers, educators, and construction professionals, ensuring that AI adoption is not just technically feasible but also socially and economically sustainable.

Table 9. Impact-timeline table—longitudinal perspective, illustrating the short-, medium-, and long-term effects of AI adoption in case studies.

Case Study	Immediate Impact (1–2 Years)	Medium-Term Impact (3–5 Years)	Long-Term Impact (6+ Years)
ChatGPT in Education	AI-assisted technical writing improves student engagement and learning outcomes.	AI-integrated curricula are refined, balancing AI-generated content with human-led critical thinking development.	AI-driven assessment becomes standard in construction education, enhancing learning adaptability.
AI in Safety Training	Enhanced hazard recognition in pilot projects, improving initial site safety measures.	AI-driven safety training platforms become more widespread, with firms incorporating AI in safety assessments.	AI-based safety training replaces traditional models in high-risk construction environments.
Maket's AI in Training	Early adopters among innovative firms benefit from efficiency improvements.	Regulatory frameworks begin to accommodate AI-driven workflows, reducing SME adoption barriers.	AI-driven training platforms become a standard feature for SMEs, supported by government and industry incentives.
STRABAG's Generative AI	Select construction firms integrate AI into design workflows for efficiency gains.	Wider adoption of AI-driven design tools as firms become more digitally literate and comfortable with AI-enhanced workflows.	AI-driven generative design becomes a norm, reducing design iteration times and improving overall project efficiency.

Table 10. Adoption barrier and mitigation strategy.

Case Study	Key Adoption Barriers	Mitigation Strategies
ChatGPT in Education	Over-reliance on AI, reducing students' ability to develop critical thinking skills independently.	Develop hybrid AI-human learning models where AI complements but does not replace instructor-led discussions.
AI in Safety Training	Resistance from experienced workers who are sceptical about AI's role in safety training.	Phased AI adoption strategy, beginning with AI-assisted safety monitoring before moving to fully automated AI training.
Maket's AI in Training	High cost of AI training platforms, limiting accessibility for SMEs and smaller firms.	Government incentives and subsidies for AI training in SMEs, along with industry-led AI competency development programs.
STRABAG's Generative AI	Complex integration requirements and lack of AI literacy among construction professionals.	Structured AI upskilling programs for construction teams, and phased integration of AI within BIM and project workflows.

Together, these three tables offer a holistic and structured approach to evaluating AI integration in construction education, training, and professional practice. The matrix-style table contextualises AI within strategic frameworks, the impact-timeline table provides a longitudinal adoption perspective, and the adoption barrier table proposes targeted solutions to ensure scalable and effective AI implementation. These discussions highlight the interplay between technological advancements, industry readiness, and policy evolution, ultimately guiding future research and decision-making on the sustainable adoption of AI in the built environment.

The scalability of AI applications across different construction contexts is a critical consideration for their widespread adoption. The findings from this study indicate that AI-driven tools exhibit strong adaptability but face distinct challenges when applied to large-scale infrastructure projects versus smaller-scale residential construction. AI applications such as viAct's AI-powered safety training and Buildots' AI-driven progress tracking demonstrate high scalability for large infrastructure projects, where real-time hazard detection and automated progress monitoring provide significant efficiency gains. These applications are well-suited to high-budget, complex projects that involve multiple stakeholders, extensive data integration, and compliance-driven workflows. Conversely, AI applications in residential construction and SME-driven projects require more cost-effective and modular AI solutions. Tools such as Digs AI for renovation planning and Maket's generative AI for training show strong potential for smaller projects by enhancing design efficiency, workforce upskilling, and renovation planning. However, challenges such as high upfront costs, lack of AI literacy among smaller firms, and limited regulatory standardisation hinder their broader implementation. PESTEL analysis further highlights economic constraints that disproportionately affect smaller-scale construction firms, which may lack the financial flexibility to integrate advanced AI tools effectively.

The sector-specific adoption of AI is further influenced by project scale, complexity, and risk tolerance. Infrastructure megaprojects benefit from AI's predictive analytics, real-time risk assessment, and large-scale workflow automation, while residential construction and SME operations require customisable, user-friendly AI solutions that integrate with existing workflows without extensive retraining. This differentiation underscores the need for scalable AI frameworks that are flexible enough to accommodate both large and small construction contexts.

Addressing skill gaps requires integrated learning pathways that align education, training, and practice. AI-enhanced curricula incorporating virtual training modules and real-time project applications could ensure a seamless progression of competencies. Scenario planning highlights that high adoption of AI could revolutionise skill development, creating unified platforms that bridge educational theory, practical training, and professional application. The adoption of AI in construction presents ethical and regulatory challenges that must be addressed to ensure responsible and sustainable integration. Key concerns include data privacy, algorithmic bias, liability in AI-driven decision-making, and regulatory compliance. AI tools such as ChatGPT for education, viAct's safety monitoring, and STRABAG's generative design models rely on large datasets that may include sensitive information, raising questions about data security and access control. Additionally, the risk of algorithmic bias in AI-generated recommendations could lead to unintended disparities in safety assessments, training outcomes, and project planning.

Regulatory frameworks for AI in construction remain fragmented and inconsistent across different jurisdictions, with large-scale infrastructure projects facing more stringent compliance requirements compared to smaller residential projects. The PESTEL analysis highlights how evolving government policies and industry standards play a crucial role in determining AI's long-term adoption. To mitigate these challenges, construction firms and policymakers should establish transparent AI governance frameworks, enforce explainable AI (XAI) models to reduce bias, and implement regulatory adaptation strategies that align AI integration with existing compliance and safety standards. Future research should focus on developing industry-specific AI regulations and best practices, ensuring fair, accountable, and ethically responsible AI adoption in construction.

8. Conclusions

The integration of generative AI, LLMs, and ChatGPT into the construction industry offers transformative potential to address skill gaps and inefficiencies in education, training, and practice. However, significant discrepancies between these domains must be addressed to maximise AI's impact. Education should incorporate AI-enhanced tools such as generative design platforms and virtual reality modules into curricula, fostering interdisciplinary learning that blends theoretical knowledge with practical, hands-on experience.

Training must evolve to leverage AI-driven tools like immersive virtual environments and predictive analytics to enhance workforce readiness. Programmes should go beyond task-specific skills to include leadership and strategic competencies, ensuring workers are equipped to adapt to technological advancements.

In practice, embedding AI tools into workflows can optimise resource allocation, improve safety, and enhance collaboration. Developing scalable AI frameworks adaptable to diverse environments will be critical for broader adoption. Organisations must also invest in upskilling initiatives to enable professionals to effectively utilise AI for decision-making and strategic planning.

Collaboration between academia and industry is essential to address ethical and practical challenges, including algorithmic bias, data privacy, and interoperability. Establishing robust governance frameworks and ensuring equitable access to AI technologies are critical for sustainable adoption. Scenario planning highlights that high AI adoption can unify education, training, and practice, enabling the construction sector to achieve sustained growth, innovation, and competitiveness.

By aligning education with industry needs and fostering collaboration, the construction industry can create a future-ready workforce. This approach not only addresses existing skill gaps but also positions the sector to fully embrace the opportunities of Construction 4.0, ensuring long-term success and resilience. The study's findings reinforce that while AI tools exhibit strong potential for large infrastructure projects, their adoption in small-scale construction requires additional considerations, including cost accessibility, ease of integration, and workforce AI literacy. Future research should focus on developing modular AI solutions tailored for SMEs and residential construction, ensuring that the benefits of AI-driven automation, safety monitoring, and training enhancements can be realised across diverse construction sectors.

This study's scope was intentionally designed to provide an in-depth exploration of AI applications in construction education, training, and practice through comparative case study analysis, focusing on the qualitative dimensions of AI adoption rather than empirical quantification. The reliance on literature review and descriptive case analyses allowed for a detailed examination of contextual factors, challenges, and opportunities associated with Generative AI, ChatGPT, and LLMs in the construction sector. However, a key limitation is the absence of quantifiable indicators or statistical analyses to substantiate the research findings. While the structured comparative framework enables systematic evaluation across multiple domains, the lack of empirical performance metrics, statistical modelling, or longitudinal data analysis restricts the study's ability to draw definitive conclusions on AI's measurable impact on efficiency, learning outcomes, and productivity. Future research should complement this qualitative depth with quantitative validation, incorporating surveys, experimental studies, and statistical benchmarking to enhance the robustness, replicability, and generalisability of AI adoption insights in construction. The study does not fully address potential biases in AI-generated content, the ethical implications of AI-driven decision-making, or concerns regarding workforce displacement. Additionally, ethical considerations must be acknowledged in the study's approach. Since all case study data were publicly available, the research adhered to ethical guidelines regarding data usage, privacy, and transparency.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AR	Augmented Reality
BIM	Building Information Modelling
GDPR	General Data Protection Regulation
IoT	Internet of Things
LLM	Large Language Models
PESTEL	Political, Economic, Social, Technological, Environmental, and Legal

SDG	Sustainable Development Goal
SME	Small and Medium-Sized Enterprises
SWOT	Strengths, Weaknesses, Opportunities, and Threats
VR	Virtual Reality

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