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Review

Generative AI Applications in Architecture, Engineering, and Construction: Trends, Implications for Practice, Education & Imperatives for Upskilling—A Review

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Abstract: This study investigates the current landscape of generative AI and LLM applications in architecture, engineering, and construction (AEC), focusing on trends, practical implications, educational strategies, and imperatives for upskilling. Employing a six-stage systematic review sourced from Google Scholar, Scopus and Web of Science, 120 papers were analyzed to provide a comprehensive understanding of the role of these technologies in shaping the future of the AEC industry. By addressing these objectives, the research contributes to enhancing knowledge about the potential impacts of generative AI and LLMs on the AEC industry and provides insights into strategies for leveraging these technologies effectively. This study underscores the transformative impact of AI and advanced technologies on the AEC sector and education. By enhancing learning experiences and optimizing construction processes, AI fosters personalized education and efficient project management. The study's significance lies in its identification of necessary skills and competencies for professionals, ensuring effective AI integration. Implications include the need for continuous professional development, formal education, and practical training to leverage AI's potential fully. This paves the way for sustainable, intelligent infrastructure and accessible, adaptive learning environments, driving innovation and efficiency in both fields.

Keywords: generative AI; LLM; architecture; engineering; construction; trends; practice; education; upskilling

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1. Introduction

The AEC sector has undergone significant transformations, characterized by the rise of novel technologies aimed at enhancing learning, productivity and effectiveness [1,2]. In particular, the educational sector is experiencing profound change [3]) through the fusion of artificial intelligence (AI), big data analytics, the Internet of Things (IoT) and cloud computing [4,5]. State-of-the-art technologies have become necessary to address the changing requirements of 21st-century education [5,6]. Subsequently, the increasing need for sustainable, intelligent and durable infrastructure has hastened the integration of AI and other technologies within the AEC industry. In recent years, AI has advanced swiftly, finding applications across various fields. AI systems can emulate human thought processes and handle repetitive tasks with extensive data [7]. AI has been employed in education to improve administrative functions and academic assistance, emerging as a driving force for educational change, presenting the opportunity to tailor learning experiences based on the specific needs and preferences of each learner [8–10].

AI's growth in education stems from its ability to analyze large data sets and create insights guiding personalized learning paths [11]. Through individual learning behaviors, inclinations and capabilities, AI empowers educators to customize content and experiences to meet the distinct requirements of every student [12,13]. AI systems analyze extensive datasets to detect patterns, relationships, draw inferences, offer recommendations and initiate actions [2]. With AI tools in place, education expenses are reduced by automating tasks and providing streamlined learning experiences. This affordability can expand access to higher education for students from low-income backgrounds or those facing financial challenges with learning [14,15]. Incorporating AI not only supports personalized learning but also empowers adaptive systems that adjust in real-time to the learner's advancement, enhancing educational efficiency and effectiveness [16,17]. The use of AI chatbots like Generative Pretrained Transformer (ChatGPT) models has fundamentally transformed the understanding and implementation of learning assessment [18]. The merging of human intellect and AI enhances the augmentation of learners' cognitive skills, surpassing conventional educational limitations [4].

GPTs can perform various tasks including generating language, analyzing sentiment, categorizing text and answering questions [19]. The large language model (LLM) captures extensive data to produce human-like responses to user queries. It has garnered substantial interest from researchers for its adeptness in text generation and knowledge acquisition [2]. ChatGPT has over 100 million global users and has received over 10 billion website visits from these users; 64.53% fall within the 18 to 34 age bracket, with an additional 17.65% aged 35 to 44, totaling over 82% of users under 45 years old [18]. Within education, GPT could revolutionize self-directed learning by offering personalized assistance, enhanced accessibility, flexible study options, instant feedback, and guidance [20].

In construction, GPT models have demonstrated their usefulness in identifying tasks and creating schedules tailored to project needs. Consequently, during the pre-design phase, GPT models offer the potential for analyzing data and furnishing pertinent insights to project managers. Through learning, GPT serves as a repository of industry standards and insights gleaned from past projects incorporated in aiding stakeholders in making informed decisions [21,22]. Likewise, Wang et al. [23] noted that ChatGPT functions as a resource for fundamental knowledge, offering varied viewpoints, identifying evident errors and promptly proposing pathways for enhancement. The potential of tailored, instant training and feedback provided by ChatGPT can significantly reshape engineering education and training initiatives. Consequently, there arises a necessity for an informative, adaptive, and inductive educational approach for AEC students and professionals, leveraging generative AI and utilizing ChatGPT. The integration of generative AI into architecture, engineering, and construction (AEC) workflows represents a significant advancement in the industry's digital transformation. It offers a myriad of opportunities to improve processes, enhance innovation, and optimize project outcomes. For instance, in architecture, generative AI models can be used to rapidly conceptualize and visualize design concepts based on specific requirements and constraints [24]. Leveraging Natural language processing (NLP), architects can explore and iteratively review diverse design options before finalizing decisions, fostering creativity and informed decision-making. In engineering, technical specifications, calculations, and simulations can be generated swiftly (Li et al., [25], enabling civil engineers to expedite structural analysis reports, optimize designs for cost and material efficiency, and even generate automation and control systems code. This capability has the potential to accelerate the design and development processes, facilitating more innovative solutions. During the planning and construction phases, generative AI can be used to optimize project management workflows. AI-generated schedules can be created, refined, and seamlessly integrated into the project management process, saving substantial time and effort compared to manual scheduling methods [26]. Furthermore, comprehensive project documentation, including scope, resource availability, constraints, risk assessments, and safety plans, can be generated and reviewed using AI. By providing project details and requirements, AI models can generate comprehensive documentation adhering to industry standards and regulations [24], mitigating risks, fostering effective communication among stakeholders, and enhancing overall project management. However, the effective integration of generative AI and tools like ChatGPT into AEC workflows requires a comprehensive skill set among professionals. Generative AI (Artificial Intelligence) and large language models (LLMs) have the potential to radically transform the architecture, engineering, and construction (AEC) industry in the years to come. While considerable research activity is already underway to address new sets of emerging challenges in the built environment, the implications of the breakthroughs in generative AI and LLMs for the profession at large have not been meaningfully summarized in the literature. Hence this study examines generative AI and LLMs from the perspective of trends in applications, challenges and opportunities they offer the industry, educational approaches, skills and competencies. The objectives are the following:

i. How are generative AI and LLMs currently being applied in architecture, engineering, and construction (AEC) practices, and what are the predominant trends?
ii. What specific practical challenges and opportunities do generative AI and LLMs present for AEC professionals in terms of design, project management, and sustainability?
iii. What educational approaches should be adopted in preparing AEC students and professionals to utilize generative AI and LLM technologies in their work?
iv. What are the key skills and competencies required for AEC professionals to effectively integrate generative AI and LLMs into their workflows, and how can these skills be developed?

Section 2 discusses the method adopted, Section 3 examines the trends and applications while Section 4 investigates the challenges and opportunities offered by generative AI and LLMs. The findings and discussion continue into Section 5 on educational approaches, skills and competencies in Sections 6 and 7 concludes the study.

2. Materials and Methods

The study aimed to examine the trends, implications for practice, education, and upskilling imperatives related to the adoption and application of generative AI in the AEC industry. To achieve this, a literature review was conducted using a six-stage systematic review process, similar to the one utilized by [14]. This approach was considered thorough and suitable for addressing the study's objectives. It has been adopted in previous studies, such as those by [14] on BIM implementation efforts and approaches in selected countries and by Onososen et al. [27].

The six-stage review process involves the following: defining the review scope (stage one), identifying relevant literature (stage two), collecting data (stage three), evaluating the quality of the literature (stage four), analyzing the data (stage five), and interpreting the results (stage six). This method ensures the identification and selection of relevant articles essential for addressing the study's objectives.

In stage one, the review scope was defined, focusing on examining the trends, implications for reskilling, and practice concerning the adoption of generative AI in the AEC industry. The databases used for the search included Scopus, Web of Science, and Google Scholar, ensuring a comprehensive selection of documents as these databases cover the academic literature relevant to the AEC industry.

The second stage involved implementing a search strategy to identify relevant literature. The predefined search strategy included journal articles, conference papers, and book chapters. Keywords such as "generative AI", "ChatGPT", "LLM", "opportunities", "challenges", "trends", "skills", "education", "learning", and "competencies" were used to retrieve pertinent data [28]. Previous literature-based reviews, such as those by Nwankwo et al. [29] and Tjebane et al. [30], have adopted similar strategies.

Following these strategies, the subsequent steps—data collection and quality evaluation—were carried out to gather and assess relevant, credible articles and documents. The fifth step involved data analysis, where text analysis was performed to identify trends and explore implications for practice, education, and upskilling requirements. The final step was the interpretation of the results based on this analysis [28]. This approach was deemed comprehensive, providing thorough insights into the study's objectives. A total of 120 selected papers was used to address the study's objectives, as discussed in Sections 3–6. The research method is outlined in Figure 1 below.

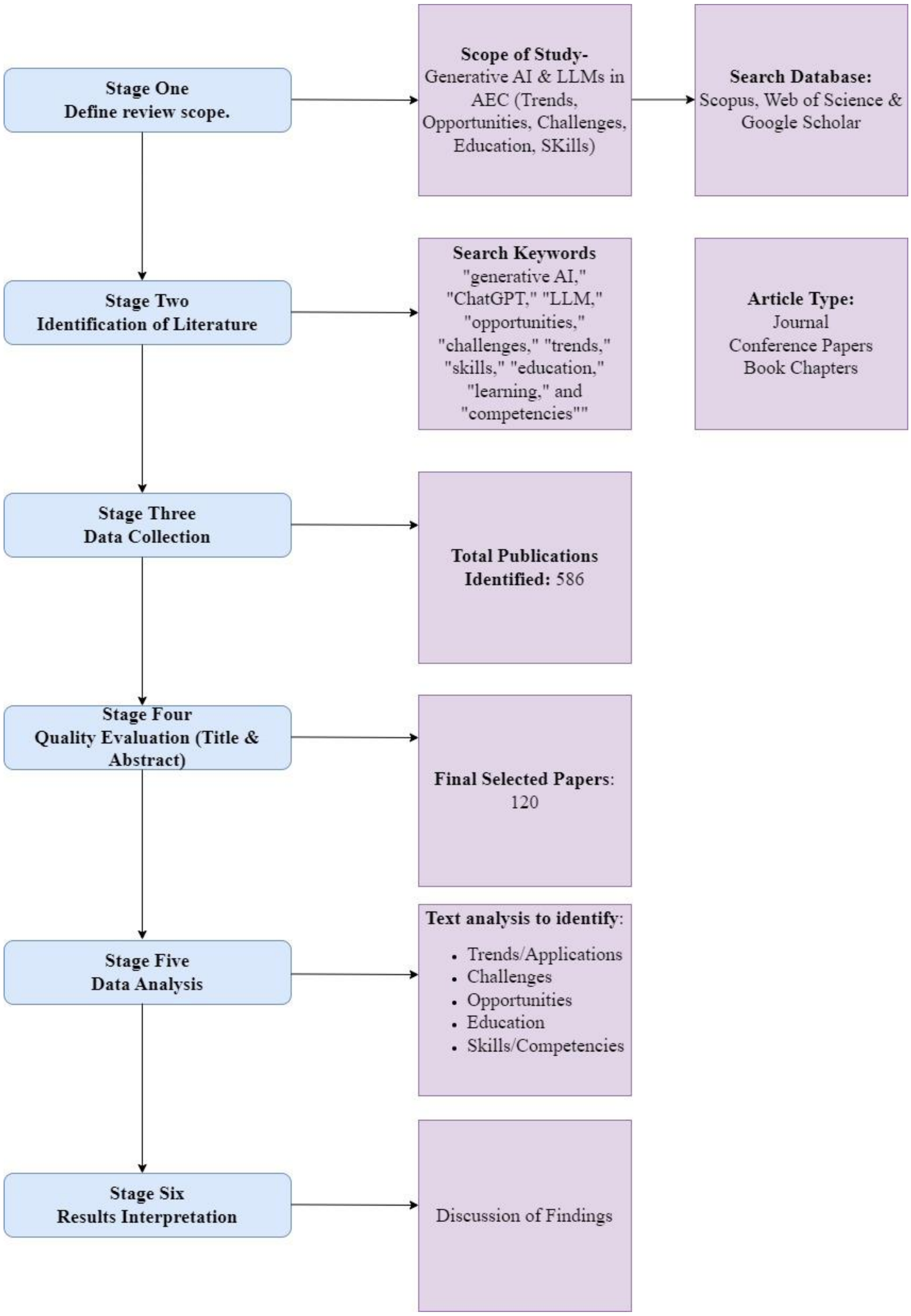

Figure 1. Six-Stage Systematic Review Process.

3. Trends and Applications of Generative AI and LLM in Architecture, Engineering, and Construction (AEC) Practices

The introduction of large language models (LLMs) and generative AI has unlocked a new realm of possibilities for optimizing workflows and fostering innovation within the architecture, engineering, and construction (AEC) industry. These sophisticated AI models possess the remarkable ability to generate original content based on user input, holding the potential to transform various facets of AEC practices. By capitalizing on the power of natural language processing and the extensive knowledge embedded within their vast architecture, LLMs can be employed to support a wide array of tasks in the AEC domain, ranging from conceptual design to project management and beyond. A key application of generative AI in AEC is in the domain of generative design and optimization. This involves using algorithms to explore a broad spectrum of design possibilities and generate numerous design alternatives based on predefined criteria and constraints, enabling architects and engineers to efficiently assess multiple options and achieve optimized designs [31].

Generative adversarial networks (GANs) have shown significant potential in architectural design generation [25]. GANs, first introduced by [32], consist of two competing neural networks: a generator and a discriminator. The generator's role is to create new synthetic data, while the discriminator's task is to distinguish between real and generated data [33]. By leveraging these advanced AI technologies, the AEC industry can push the boundaries of traditional design methods and achieve unprecedented levels of efficiency and creativity.

Generative adversarial networks (GANs) have emerged as a powerful tool in the field of generative artificial intelligence, enabling the creation of realistic and diverse outputs across various domains. In the context of architecture, engineering, and construction (AEC), GANs have been increasingly employed to automate and optimize design processes, leading to significant advancements in project conception, planning, and execution [34]. GANs operate within a framework where a generative network learns to generate candidates of interest, while a discriminative network distinguishes the generated candidates from the ground truth [32,35]. This adversarial training process allows GANs to produce outputs that closely resemble real-world examples. In the AEC industry, GANs have been applied to tasks such as generating floor plan layouts [36], This method highlights the potential of GANs to automate and enhance space planning tasks, offering architects new tools for creative and efficient design. In addition to GANs, evolutionary algorithms like genetic algorithms (GAs) are extensively used for design optimization within the AEC domain. GAs emulate the process of natural selection, exploring a vast design space to identify optimal solutions [37]. A pertinent application of GAs is in the optimization of hospital room layouts. The study by Calixto and Celani, [38] employed GAs to address various design considerations, such as adjacent requirements, circulation efficiency, and natural lighting. Their study concluded that GA-optimized layouts surpassed manually designed ones in terms of both functionality and efficiency.

Further advancing the use of GANs, Liao et al. [39] introduced StructGAN, a method designed to facilitate the structural design of high-rise shear wall residential buildings. StructGAN effectively translates architectural elements into structural designs, ensuring that the resulting structures are both safe and cost-effective. Evaluated through computer vision and engineering expertise, the designs generated by StructGAN were found to be comparable to those optimized by seasoned engineers, underscoring the potential of GANs to revolutionize structural engineering practices.

ChatGPT, driven by the advanced GPT architecture, exemplifies the transformative impact of Artificial Intelligence (AI) on design and Building Information Modeling (BIM) processes [40]. These technologies are at the forefront of a paradigm shift, enhancing efficiency, creativity, and collaboration within the architectural and construction sectors. A pivotal contribution of LLMs and other generative AI models in BIM is their ability to generate intricate and contextually relevant textual and visual information, significantly aiding various phases of architectural and construction projects [11]. Generative AI in BIM plays a crucial role in the ideation phase of architectural projects. These AI models analyze extensive datasets of existing architectural designs, construction methods, and materials, drawing valuable insights from both historical and contemporary examples. By comprehending successful design and construction techniques, these models assist architects in generating innovative and contextually appropriate design solutions, fostering creativity while ensuring adherence to practical and aesthetic considerations [11]. The influence of generative AI extends beyond ideation into practical applications within BIM. Recent advancements have seen the integration of chatbots and other AI tools for various tasks. For instance, these tools are employed for data and information retrieval, enhancing accessibility and efficiency in managing project information [41,42]. Furthermore, AI-driven chatbots are utilized for summarizing construction contracts, providing concise and comprehensible summaries that facilitate decision-making processes [43]. Real-time project updates are another area where generative AI has made significant strides. AI tools offer timely and accurate updates on project status, enabling better project management and coordination [44], question-and-answer systems powered by AI enhance communication and knowledge sharing among project stakeholders [41] and safety training is also noteworthy, as it offers interactive and personalized training modules, improving safety standards and awareness on construction sites [45].

Generative AI models have become crucial for automating laborious and repetitive tasks within the Building Information Modeling (BIM) workflow, significantly boosting productivity in the architecture, engineering, and construction (AEC) sectors [11,46]. The integration of generative AI and large language models (LLMs) in AEC is driving a significant shift in workflow, allowing professionals to spend more time on creative activities. Traditionally, much of the workflow in AEC has been consumed by repetitive and time-intensive tasks, such as drafting, data analysis, and documentation. With the advent of generative AI, these tasks can now be automated or significantly accelerated, freeing up professionals to focus on more strategic and creative aspects of their work. For instance, AI-driven tools can quickly generate multiple design options, optimize structural layouts, or analyze vast amounts of data for decision-making, all of which would have previously required substantial manual effort. This shift not only enhances efficiency but also enables architects, engineers, and construction managers to explore more innovative solutions, engage in complex problem-solving, and experiment with new design ideas. The result is a more dynamic and flexible workflow where the emphasis moves from routine execution to creative exploration and refinement. This transition is also crucial for the development of new skills, as professionals are required to adapt to these advanced tools, leading to a greater focus on continuous learning and upskilling in the industry. The shift towards more creative activities is therefore not just a consequence of technological advancement but also a driver of further innovation and professional growth within AEC. These models can create detailed 3D models and architectural drawings from basic sketches and contextual descriptions, speeding up the design process and allowing professionals to focus on more intricate and creative elements of their projects. Advanced integration techniques, like those exemplified by BIM-GPT, demonstrate that effectively leveraging large language models (LLMs) can unlock valuable insights from extensive construction data assets. This integration highlights the potential of LLMs to enhance various aspects of BIM, from data extraction to design automation [33]. In safety management, [47] made a notable contribution to construction safety by introducing an innovative method for classifying injury narratives to identify construction risks and hazards. Their approach, which utilizes fine-tuned BERT sentence-pair models, represents a significant advancement in the processing and analysis of large-scale textual data related to construction safety, improving hazard identification and risk management. The study by Zheng and Fischer [42] proposed a novel methodology involving a virtual assistant designed for BIM information retrieval through natural language interfaces. This virtual assistant improves the efficiency of information retrieval and user interaction by handling natural language queries and accessing BIM databases, thus enhancing user experience and data accessibility within BIM workflows. In another notable development, Chang and Cheng [48] explored the rapid design of component cross-sectional dimensions for steel frame structures through a case study. Utilizing the GNN-based NeuralSim and NeuralSizer modules, they demonstrated that the NeuralSizer module could generate new designs in just 10.07 milliseconds. This rapid design capability, coupled with the integration of NeuralSim constraints, underscores the algorithm's robust generalization ability [39].

Further advancing the application of AI in structural design, Jeong and Jo [49] employed deep reinforcement learning to generate and optimize frame beam designs. Their method was applied to a two-dimensional, three-story, three-span reinforced concrete frame structure, illustrating the efficacy of reinforcement learning in optimizing complex structural designs. The study by Zhao et al. [50] proposed an innovative approach to frame structure design by using graph representation methods. They developed a novel graph neural network model for beam layout design, leveraging the topological characteristics of graphs in beam-column connections. Their approach achieved high accuracy in test results, comparable to designs created by experienced engineers, and demonstrated the utility of data-driven geometric deep learning algorithms in generating large-scale datasets for training neural networks. The emergence of generative AI as a transformative force in structural optimization has empowered built environment professionals to make data-driven decisions and push sustainable design boundaries [35]. By harnessing the power of real-time environmental data and extensive material databases, these intelligent algorithms offer unprecedented insights into the ecological impact of various construction materials and methods [51]. This paradigm shift in structural engineering allows professionals to meticulously evaluate the carbon footprint, energy consumption, and recyclability of different design choices, enabling them to prioritize environmentally friendly solutions. Generative AI algorithms serve as a catalyst for this green revolution, with potential to analyze huge datasets and characterize ideal design parameters that minimize the building's environmental impact.

4. Predominant Trends

The emergence of innovative technologies, particularly generative Artificial Intelligence (AI), has transformed the landscape of energy-efficient construction practices. Among the most notable advancements is ChatGPT, developed by OpenAI, which has revolutionized AI-driven conversational agents [11]. This sophisticated language model holds immense potential in reshaping the approach of architects, engineers, and construction professionals towards designing and planning buildings, ultimately fostering the creation of more sustainable and cost-effective solutions. One of the most significant contributions of ChatGPT and other generative AI models to energy-efficient construction lies in their remarkable ability to process and analyze enormous amounts of data from a wide array of sources, encompassing climate patterns, energy consumption statistics, and architectural designs. By delving deep into this data, these AI systems can uncover hidden patterns and trends that may be difficult for human analysts to detect [52]. This comprehensive analysis empowers professionals to make well-informed decisions that prioritize sustainability and energy efficiency. The power of advanced language models (LLMs) like ChatGPT extends beyond mere data analysis. These models have the ability to effectively handle large quantities of unorganized data, generating significant insights with exceptional speed and simplicity. By analyzing building codes and regulations, generative models can identify relevant requirements and generate concise, customized reports to architects. This eliminates the need for time-consuming manual reviews and simplifies the design process, while also ensuring compliance with energy-efficient standards [33].

Moreover, contractors have started harnessing the capabilities of AI by inputting design specifications into these systems, which can then automatically generate cost and schedule estimates by linking 3D models with external databases. This seamless integration of design and cost data facilitates a more precise evaluation of the financial implications associated with energy-efficient construction choices. Material names, soil kinds, concrete strengths, roof slopes, furniture suppliers, last changed dates, and sophisticated analytical inquiries are all made easily available to stakeholders by AI's natural language capabilities. To help professionals make educated decisions, generational AI facilitates data flow across the actual and virtual worlds of the built environment [33]. Whether it is obtaining wind load estimates, connecting designs to cost data, or producing code requirements from regulations, GenAI streamlines information collection and analysis, giving architects and engineers the power to optimize designs for optimum energy efficiency. Researchers have also explored the potential of transformer models like ChatGPT in project management. A study by Chen et al. [53] assessed the consistency, scalability, and adaptability of ChatGPT responses by providing detailed project scope inputs and evaluating the model's capacity to generate task lists and project schedules. The results demonstrated ChatGPT's ability to effectively handle modifications, larger projects, changing requirements, and unforeseen challenges, streamlining project management processes and adapting to evolving project needs with remarkable consistency and scalability. In the domain of construction safety, Uddin et al. [54] carried out a study involving 42 construction program students to investigate the impact of ChatGPT on hazard recognition ability. By comparing the students' performance before and after the introduction of ChatGPT, the researchers aimed to enhance safety management in construction workplaces. The findings suggest that AI-driven conversational agents can play a crucial role in improving hazard recognition skills and fostering safer construction practices.

Construction automation faces a significant challenge in maximizing the efficiency of robotic systems, particularly in developing efficient sequence planning for construction tasks. To tackle this issue, You et al. [55] introduced RoboGPT, a robotic system that leverages ChatGPT-4 for automated sequence planning in complex construction assembly tasks. By breaking down tasks into logical steps and considering spatial and resource constraints You et al. [55] RoboGPT generated optimized assembly sequence plans for structural component assembly, electrical and plumbing system installation, and construction equipment coordination. Furthermore, Smetana et al. [56] employed OpenAI's GPT-3.5 model to enhance text-based incident analysis using data from OSHA's Severe Injury Reports (SIR) database in the context of highway construction safety. The analysis identified major accident types, such as heat-related and struck-by injuries, and revealed commonalities between incidents, offering valuable insights for improving safety measures in highway construction [56].

The selection of materials plays a pivotal role in mitigating the environmental impact of construction projects. Designers must carefully consider a multitude of factors, including cost constraints, location, design requirements, and environmental regulations, to make informed decisions that prioritize sustainability. To navigate this complex landscape, optimization approaches such as mixed integer optimization and GPT models integrated with Building Information Modeling (BIM) have emerged as powerful tools for conducting detailed evaluations and generating alternative design solutions that minimize the ecological footprint of construction activities [19]. One of the most notable applications of text-to-text generative AI in the pre-construction phase is its ability to synthesize comprehensive feasibility reports. By analyzing vast amounts of data and generating concise, actionable insights, this technology streamlines the decision-making process, enabling stakeholders to make informed choices that align with sustainability goals. Moreover, generative AI assists in the documentation of regulatory compliance, ensuring that projects adhere to the latest environmental standards and guidelines. It also supports the preparation of compelling proposals and bids, which are essential for securing project approval and initiating construction activities [57]. During the construction phase, text-to-text generative AI plays a crucial role in monitoring daily project progress and refining construction specifications. By continuously analyzing data from various sources, such as sensors, reports, and communication channels, this technology ensures that the project remains on track and adheres to the designated materials, methods, and standards. This real-time monitoring and optimization help to minimize waste, reduce energy consumption, and optimize resource utilization, contributing to a more sustainable construction process. In addition to monitoring progress, text-to-text generative AI supports task assignments and enhances team communication. By analyzing project requirements, available resources, and team member skills, this technology can generate optimized task allocations and provide clear, concise instructions to team members. This streamlined communication and coordination improves operational efficiency, reduces misunderstandings, and minimizes rework, ultimately leading to a more sustainable and cost-effective construction process. As the project moves into the post-construction phase, text-to-text generative AI continues to provide valuable support. It contributes to the creation of detailed as-built documentation and maintenance manuals, which are essential for the ongoing operation, maintenance, and management of the facility. By generating accurate and comprehensive documentation, this technology ensures that the building continues to perform optimally and maintains its sustainability features throughout its lifecycle.

Text-to-video generative AI models have emerged as a powerful tool for creating engaging and informative content in the construction industry. These models generate introductory and concept animation videos from textual descriptions, providing stakeholders with a vivid understanding of potential sites and project concepts. By transforming written ideas into dynamic visual representations, generative AI bridges the gap between abstract concepts and tangible reality, enabling stakeholders to grasp the essence of a project more effectively. One of the key trends of text-to-video models is the creation of dynamic animations that offer a visual preview of the proposed construction. By inputting textual descriptions of the project, generative AI produces detailed and realistic animations that showcase the building's design, layout, and features. These animations serve as a powerful communication tool, allowing stakeholders to visualize the project's potential and provide early feedback. This iterative process of visualization and feedback helps to refine the design, ensuring that the final product aligns with the stakeholders' vision and expectations. In addition to concept visualization, text-to-video models also generate detailed step-by-step video guides for equipment operation and safety procedures. By leveraging instructional texts and safety manuals as input, generative AI creates engaging and informative videos that demonstrate the correct use of construction equipment and highlight important safety protocols. These videos not only streamline the training process for workers but also enhance adherence to safety standards by visually depicting correct practices and potential hazards. By providing a clear and accessible format for conveying complex information, text-to-video models contribute to a safer and more efficient construction site.

As the project moves into the post-construction phase, generative AI continues to provide valuable support through the production of facility usage instructional videos and building update videos. These videos summarize important changes and operational guidelines, ensuring that facility managers and stakeholders have access to the most up-to-date information. By presenting this information in a visually engaging format, generative AI enhances the effectiveness of communication and facilitates the smooth operation and maintenance of the building. Alongside text-to-video models, generative AI also leverages image-to-image models to significantly enhance visualization capabilities across various project phases. During the pre-construction phase, AI-driven architectural image translation adapts visualizations to different styles, allowing for creative and cultural customization. This enables designers to explore a wide range of aesthetic possibilities and tailor the project's appearance to suit the client's preferences and the local context. Moreover, generative AI refines site planning by transforming satellite imagery into detailed site diagrams. This process involves analyzing high-resolution satellite images and extracting relevant features, such as topography, vegetation, and existing structures. By generating accurate and detailed site diagrams, generative AI supports informed decision-making and facilitates the development of comprehensive project plans. Coming into concept generation, image-to-image models produce multiple architectural sketches based on initial design inputs. This allows architects and designers to explore a broader array of design possibilities, sparking creativity and innovation. By generating diverse visual interpretations of a concept, generative AI helps to identify the most promising design directions and enhances the decision-making process. Throughout the construction phase, generative AI plays a crucial role in keeping architectural drawings up-to-date. By processing real-time images from the construction site, these models detect changes and automatically update the corresponding drawings. This ensures that the documentation remains accurate and current, reducing the risk of errors and inconsistencies. Another trend of image-to-image models in the construction phase is the matching of construction material textures to reference images. By analyzing the visual characteristics of the desired materials and applying them to digital models, generative AI helps to maintain visual consistency and quality throughout the project. In the post-construction phase, generative AI assists with damage assessments by processing images of affected areas and suggesting visualized repair strategies. By identifying and quantifying the extent of damage, these models generate detailed reports and propose targeted repair solutions. This not only expedites the assessment process but also helps to prioritize maintenance efforts and optimize resource allocation. Finally, image-to-image models support landscape transformation visualization, enabling stakeholders to envision how the completed project will integrate into its surrounding environment. By generating realistic renderings that incorporate the proposed landscaping and site modifications, generative AI helps to ensure that the project harmonizes with its context and contributes to the overall aesthetic appeal of the area. Some generative AI Algorithm applications are presented in Table 1 below.

Table 1. Generative AI Algorithm Applications.

Author	Generative AI Algorithm			AEC Application	Type
	GAN	Graph Generative Netwok	Transformer Models		
Liao et al. [39]	Y			Structural system	-
Zhao et al. [52]	Y			Structural system	-
Liao et al. [39]	Y			Structural system	-
Zhao et al. [50])		Y		Structural system	-
Zhao et al. [50]		Y		Structural system	-
Chang & Cheng [17]		Y		Structural system	-
Liao et al. [39]		Y		Structural system	-
Chen et al. [53]			Y	Scheduling	ChatGpt
Uddin [54]			Y	Safety	ChatGpt
Zheng [42]			Y	Information Modelling	BIMS-GPT
You [55]			Y	Planning	RoboGPT
Moon et al. [58]			Y	Risk management	-
Smetana et al. [56]			Y	Safety	ChatGpt
Hassan et al. [47]			Y	Safety	-
Amer et al. [59]			Y	Planning	-

4.1. Opportunities of Generative AI and LLMs for AEC Professionals

Generative AI integration, especially ChatGPT, brings revolutionary change to different sectors such as aviation, health care, tourism, manufacturing, and so on. Integration of this technology presents both opportunities and challenges for architecture, engineering, and construction (AEC) professionals across various domains. Extensive reviews on the application of AI have been limited to cost prediction, smart or green building, BIM, construction engineering management, and general domains of the AEC industry [34,60,61]. However, this has a wider scope of AI usage in the AEC industry. Presently, the trend of research is moving towards generative and conversational AI in the AEC industry [2]. Leveraging generative AI and LLMs effectively enables AEC professionals to unlock new levels of creativity, efficiency, and sustainability in construction projects. This review focuses on opportunities of generative AI and LLMs for specific domains in AEC such as design, project management, and sustainability.

4.1.1. Design

Generative AI tools can help AEC professionals explore a wider range of design options efficiently, enabling them to discover innovative solutions that may not have been considered otherwise. These innovative solutions can expedite the design phase and give architects more creative and data-driven options. It can also rapidly generate multiple design alternatives, facilitating the exploration of unconventional ideas and optimizing solutions for specific project constraints. For instance, a study designed generative AI which was modularized for altering wall composition in BIM models [62]. Also, a search engine was used to retrieve BIM objects and documents [63,64]. Generative AI could analyze historical designs and trends to create insights for new projects. Based on the process of learning from past designs through archives, architects can provide designs that resonate with clients or users and context. The study by Tsigkari et al. [65] emphasized that AI can complement the design by two approaches: creating a surrogate model to replace the conventional time-consuming design process by using a computational predictive model; and design-assisted modeling, which incorporates designer intuition to facilitate the architectural design process.

AI can assist designers in ensuring that building designs comply with standards, codes, and regulations. This can be carried out by assigning red flags on compliance issues that can prevent time and cost delays in the design phase. Similarly, AI-driven design tools can generate personalized solutions tailored to specific project requirements, client preferences, and site conditions, enabling AEC professionals to deliver more bespoke and client-centric designs [66]. AI tools have great potential to enhance the architecture industry by improving architect skills and knowledge, analyzing design quickly, and expanding design capabilities. In addition, AI can be adopted to generate different graphs, text, images, and voice-based tools archived over the years to produce formats for various projects and select the best data that applies to the specific project or task [66,67].

When AI is powered through VR and AR tools, design visualization is possible, improving the general design process. Clients and stakeholders can communicate their intents and revisions needed in the ongoing design process. For example, Sheldon et al. [68] proposed an integration of voice control and hand gestures in AR for design. The adoption of generative AI such as LLMs facilitates knowledge management by providing access to a wide range of information; however, the quality of gathered knowledge is highly dependent on the prompt [69]. LLMs can generate vast construction knowledge context and give insights to construction stakeholders. This can facilitate communication and collaboration among multidisciplinary teams by synthesizing complex information and providing insights in natural language, fostering better-informed decision-making processes.

4.1.2. Project Management

LLMs and other AI-powered assistants can automate routine tasks, streamline communication, and assist in project coordination, ultimately improving project efficiency and reducing administrative overhead. They could automate repetitive project management tasks such as scheduling, resource allocation, and progress tracking, freeing up time for AEC professionals to focus on higher-value activities [70]. The study by Zheng and Fischer [42] developed a BIM-GPT integrated framework that could retrieve, summarize, and answer BIM databases. This was used to extract extensive and complex information from BIM models. The study by Prieto et al. [21] tested ChatGPT to generate schedules and sequences that are logical and meet the project requirements. Another study suggested an innovative technique that uses bidirectional encoder representations from transformer (BERT) to fine-tune injury narratives to identify risks and hazards in the construction industry. This same approach was adopted for automatic detection of contractual risk clauses in the construction specifications.

The study by Elghaish et al. [22] used a voice assistant system to retrieve information from the BIM model while another study proposed a chatbot to track construction progress on a blockchain-based network [71] The study by Lin et al. [72] developed a question-and-answer system for BIM and artificial intelligence of things-related questions. This Q&A system was also adopted for construction-related areas [73]. Meanwhile, different systems have been developed to retrieve semantic knowledge or information for BIM models during construction tasks, and extracting building components in BIM; project management [74,75]. Other systems proposed were materials manipulation of components for BIM, fire emergency, and building regulations [62,76]. The study by Eiris-Pereira and

Gheisari [77] created a conversational AI (natural language) and employed Amazon Alexa, AWS, and Dynamo for the construction site which was intended for educational purposes.

Another advantage of ChatGPT compared to other language generation applications is the capability to automatically synthesize construction and contract documents such as drawings, reports, and specifications to unlock the value in the data. LLMs can provide real-time insights and recommendations based on project data, enabling informed decision-making and proactive risk management. Moreover, AI-powered AR or VR applications make training of construction workers on site possible, as proper visualization of designs gives a clear picture of the entire design work and construction process. This can enhance productivity and performance of workers in construction projects [25].

4.1.3. Sustainability

AI can create awareness and inform designers of the need to optimize the design for sustainability and energy efficiency by delving into the building performance data which includes daylight, energy usage, and thermal comfort. AI aids designers in the best material selection for creating sustainable building practices. It recommends sustainable design strategies to promote an eco-friendly environment. This assistance from AI creates informed decision-making by examining factors such as cost, durability, environmental, and social impact. Generated AI designs and construction process simulations help in creating more sustainable and efficient buildings. Generative AI and LLMs are vital in suggesting eco-friendly materials and also help in optimizing materials for sustainability [78].

Technology has great potential to improve creativity, critical thinking, and scholarly endeavors in the AEC industry [79] AI could analyze large datasets to identify opportunities for sustainability improvements in building design and construction. This includes optimizing energy efficiency, materials usage, and waste reduction throughout the project lifecycle. AI-driven design tools can assess the environmental impact of design decisions in real time, allowing AEC professionals to identify and address sustainability concerns early in the design process.

AI can enable buildings to adapt to changes in environmental conditions and user needs. This can optimize lighting and energy use in the buildings by understanding the time of day and occupancy. Building performance can be optimized by analyzing vast datasets across various sustainability metrics, including energy efficiency, carbon footprint, and life cycle assessment [33]. This can be used to assess existing buildings for renovation and retrofitting which help in the optimization of material reuse and ameliorate environmental impact.

AI models can assist in streamlining operations by generating automated workflows and strategies to reduce waste in construction. They also assist in urban planning, traffic management, and infrastructure optimization which contributes to sustainable cities. Generative AI aids in sustainable project execution by assisting in project scheduling, resource allocation, and cost estimation [33]. Finally, AI models help identify flaws and variances in the specifications which promote high quality and sustainable construction processes. This model can optimize the procurement process, ensure a seamless flow of materials, and reduce waste, which is important for sustainability.

4.2. Challenges of Generative AI and ChatGPT for AEC Professionals

Despite the significant opportunities of adopting generative AI and ChatGPT in the AEC industry, certain challenges are limiting AEC professionals in its adoption in the built environment. However, addressing challenges is crucial to realizing the full potential of these technologies. This review was limited to specific domains of the AEC industry including design, project management, and sustainability.

4.2.1. Design

Generative AI models require large datasets for training, which can be challenging to gather in the AEC industry due to the complexity and uniqueness of projects. Moreover, biases in the data can lead to biased outputs, potentially causing issues in design or decision-making processes. Similarly, incorporating generative AI tools like ChatGPT into existing design workflows can be challenging. AEC professionals must be willing to adapt their processes and tools to effectively leverage these new technologies [78].

AI-generated designs may lack transparency in how they arrive at specific solutions, making it difficult for AEC professionals to understand and modify the designs according to their project requirements. Although AI is increasingly influencing design decisions, AEC professionals need to understand how to navigate regulatory frameworks and ethical considerations related to safety, privacy, and environmental impact. There is a need to ensure that AI-generated designs meet safety, structural integrity, and aesthetic standards; this poses a challenge which means outputs must be validated thoroughly [78].

Another challenge is how to integrate AI-generated designs with existing architectural plans and project requirements which may require adjustments and fine-tuning to ensure coherence and functionality. For a maximum realization of the potential of these technologies, challenges such as integration complexity, data quality, and regulatory compliance are vital for its implementation. Due to vast construction knowledge, LLM models need fine-tuning to generate efficient knowledge and industry-specific insights. When it comes to enabling GenAI to satisfy the intricate and constantly evolving needs of the construction industry, knowledge infusion in this domain still needs proper investigation [44].

4.2.2. Project Management

Generative AI poses ethical challenges which include data bias, privacy, and accountability [80–82]. Ethical considerations of data privacy and bias in AI-generated content need to be carefully examined [11]. AI tools can utilize some sensitive project information and personal details of the company which presents security risks, and could result in confidentiality breaches and violations of the intellectual property of the construction company [83]. Sensitive data being handled by LLMs leads to susceptibility which may be misused and allows unauthorized access to the public [84]. The public could obtain unauthorized access to data such as safety records, BIM models, contract documents, cost estimates, and schedules of projects. This remains a complex issue that needs to be addressed by developing an ethical framework for the implementation of generative AI in project or construction management [36].

Training and operating a generative AI model adds additional costs to projects, which presents a challenge to its adoption. This usually demands high computing resources and time to run large models. GPT model development produces additional costs to stakeholders which acts as a barrier, especially to smaller construction companies [2]. Generative AI models need to be updated as materials, methods, and regulations constantly change. When recent data are not used, the models miss innovation and become unreliable. For instance, AI chatbots that were trained prior to the pandemic would not understand the effects of labor shortages and disruption in the supply chain. This necessitates retraining models on recent data which is quite expensive and complex on a large scale [33].

Another issue is interpretability, as most models cannot be understood by professionals to suit specific project needs [85]. This is because the generative AI model is black box in nature, which means its internal workings are not transparent and cannot be easily interpreted. Further research is needed to develop interpretable model architectures that help in the decision-making of stakeholders and give confidence in the use of technology [86]. Furthermore, most models generated have poor generalizability which means the model cannot be applied beyond the dataset and distributions it was trained on [87]. This poor generalizability makes it challenging to address real-world problems and make decisions. For example, a pre-trained model based on historical data may not account for weather delays, design changes, and labor availability which may not apply to similar projects [25]. Additionally, generative AI could generate false outputs or inaccurate predictions due to limited knowledge or data. Stakeholders must be able to verify the authenticity of information generated [88,89]. This in turn leads to the inability to recognize and validate the intricacies of the real world [90].

The application of GenAI presents challenges in the construction sector because of its extensive domain knowledge needs. It is still difficult to fully capture the intricate technical engineering knowledge of the sector in the structural, mechanical, electrical, plumbing, and project management domains. When handling supplies and navigating dynamic job sites, construction also largely depends on spatial reasoning and physical situational awareness, pushing the boundaries of artificial intelligence [91]. As such, the large body of knowledge around construction makes it more difficult for GenAI to derive relevant structure-activity connections from industry data. There are, nevertheless, encouraging approaches to fill in these knowledge gaps. For example, to efficiently create industry-specific insights, big language models such as GPT require contextual input adapted to the construction domain and fine-tuning [92]. Incorporating AI tools into project management systems may require significant investment in technology infrastructure and training to ensure seamless integration with existing workflows. Handling sensitive project data within AI systems raises concerns about data security and privacy breaches, necessitating robust cybersecurity measures. Access to comprehensive and accurate data on environmental factors, material properties, and energy consumption is essential for AI-driven sustainability analysis but may be limited or fragmented. Defining and quantifying sustainability goals in a way that AI models can understand and optimize presents a challenge due to the multidimensional nature of sustainability.

5. Educational Approaches to AI and ChatGPT for AEC Students and Professionals

5.1. Innovative Learning Approach

Over the years, AEC education has predominantly relied on traditional pedagogical methods, which have hindered effective communication, information management, planning, collaboration, overall efficiency and productivity within the AEC industry. Consequently, the industry's productivity and growth have remained stagnant at 13% of global GDP, increasing by only 1% annually over the past two decades [19]. With advancements in information technologies, the adoption of generative AI technologies such as BIM, 3D printing, Augmented Reality, virtual assistants and chatbots has gained notable importance. Incorporating generative AI and ChatGPT into AEC lectures, seminars and professional training can facilitate innovative learning experiences. For instance, instructors can use AI and ChatGPT to generate interactive simulations, virtual tours, design presentations, structural analysis and project planning. These technologies are crucial for supervising and controlling different aspects of projects, enhancing effectiveness, safety and sustainability [6].

AI algorithms have the capability to enable professionals to examine past project information to anticipate potential risks, enhance resource distribution and streamline scheduling processes [93]. Similarly, ChatGPT can be embraced as both professional and student-centered technology with the capability to revolutionize teaching, learning and assessment methods in higher education [15]. Significant adjustments in teaching and learning methods are crucial for graduates to adapt to the evolving economy shaped by technological transformation [94]. Many educators have criticized traditional classroom lectures, stating that they fail to adequately equip students to apply theoretical knowledge to real-world problems. As such, this approach encourages creativity, experimentation and exploration, allowing AEC students and professionals to think outside the box and develop innovative solutions to complex challenges in construction. By embracing generative AI and ChatGPT technologies, educators can foster creativity, critical thinking, and problem-solving skills among AEC students and professionals by encouraging them to explore new ideas with innovative approaches to design, construction and management.

5.2. Problem-Based Learning Approach

The primary teaching method for AEC education has progressed beyond traditional methods due to the development of digital tools. Teachers serve as facilitators of the learning process, guiding students rather than merely imparting knowledge [95]. Integrating generative AI and ChatGPT as a virtual project assistant enables students and professionals to research project requirements, generate design concepts, collaborate with team members and document project progress. Problem-based learning promotes critical thinking, collaboration and practical application of knowledge. Similarly, in problem-based learning, students collaborate in groups to pinpoint the knowledge necessary to solve intricate problems. This approach underscores learners taking charge of their learning process, where students and professionals actively seek out problems and their corresponding solutions [96].

The adoption of generative AI and ChatGPT can serve as a valuable tool for guiding students through the problem-solving process, helping them develop analytical skills and creative problem-solving strategies, thus overcoming the primary challenge of integrating problem-based learning into AEC programs, particularly among stakeholders. Implementing this approach enables efficient monitoring techniques, prompt interventions and modifications, ultimately resulting in enhanced outcomes [96].

5.3. Project-Based Learning Approach

Research comparing learning outcomes shows that project-based learning enhances problem-solving skills and leads to higher academic performance compared to the traditional approach to learning [96]. However, AEC education and practices face challenges due to the continuously changing teaching methods and project complexity in the construction industry [97]. Integrating generative AI and ChatGPT into project-based learning prepares students for solving complex real-world problems [98]. With this approach, professionals possess significant learning autonomy in managing the crucial aspects of a project and selecting the resources necessary for problem-solving [96]. Likewise, AEC students gain an understanding of the development process and essential skills [99]. Generative AI and ChatGPT can support project-based learning initiatives by assisting students and professionals throughout the project lifecycle. From conceptualization to implementation, ChatGPT can provide guidance, generate design iterations, offer feedback and improve decision-making. The study by Saka et al. [2] noted that GPT can streamline incident reporting and analysis by categorizing incidents, identifying root causes, and suggesting preventive measures on projects [2].

Adopting project-based learning with generative AI and ChatGPT enables AEC students and professionals to utilize full-scale virtual working models or prototypes for future developments, as benchmarks for scope, schedule, budgets, standards, modification plan, strategy and process enhancement [100]. The project-based model aims to challenge students' thinking by simulating real-world team management, understanding project limitations and evaluating innovative ideas [34]. Similarly, project intricacy, resource accessibility, safety risks, design alterations, and contractual obligations are identified [101]. AEC students and professionals can use generative AI to simulate construction scenarios, assess project feasibility and evaluate cost-effective alternatives. ChatGPT can assist in analyzing project constraints, risks and mitigation strategies, thus allowing both AEC students and professionals to apply theoretical concepts to practical situations and streamlining project management processes.

5.4. Collaborative Learning Approach

Collaborative learning fosters the necessary knowledge, skills, and mindset for students to excel in an interconnected world [102]. The complexity of design and advanced construction processes increasingly necessitates effective collaboration with professionals in the construction industry [103]. Integration of generative AI and ChatGPT technologies can facilitate collaborative learning experiences by enabling seamless communication and knowledge sharing among students and professionals in the AEC industry. For instance, ChatGPT can serve as a virtual discussion moderator, facilitating group discussions, brainstorming sessions, outlining project requirements and fostering practical skills development. AEC students and professionals can use ChatGPT to explore design ideas, review project plans, and share feedback. ChatGPT can facilitate collaborative decision-making processes, ensuring that diverse perspectives are considered and consensus is reached. Through information communication technology simplification processes, generative AI allows virtual models to enhance the visualization of designs and improve communication among participants [104]. Research indicates that collaborative learning positively impacts students, enhancing knowledge acquisition, self-esteem and conflict management skills [105].

AEC educational programs should aim to integrate generative AI and ChatGPT technologies to enhance collaborative design and management approaches to construction. Collaborative methods leverage diverse skills and knowledge to create innovative solutions [103]. AI and ChatGPT can utilize inputs from project teams and stakeholders to outline the specifics of project execution, monitoring and control [2]. It can help bridge knowledge gaps, encourage diverse perspectives, and facilitate collective problem-solving in AEC projects. This approach promotes teamwork, communication and interdisciplinary collaboration among individuals from different backgrounds and expertise to solve complex AEC problems with the assistance of generative AI and ChatGPT technologies. The objective of the collaborative learning approach is to enhance problem-solving efficiency and achieve superior results [106]. Project teams can work together to achieve optimal solutions within constraints of time, budget, and resources [107]. Without generative AI and ChatGPT technologies, future AEC students and professionals may lack optimal preparation to contribute to innovative infrastructure development.

6. Key Skills and Competencies

6.1. Technical Proficiency in Core Concepts Relating to AI

To integrate generative AI into AEC works, professionals must possess a foundational understanding of artificial intelligence, including core concepts such as machine learning, deep learning, natural language processing, and generative design. This knowledge is essential for recognizing the potential applications of AI within the AEC domain and for making informed decisions about AI adoption [108]. By understanding how AI works, professionals can understand how best to leverage this tool in their everyday workflows. As AI technologies continue to evolve, it is crucial for AEC professionals to acquire a comprehensive understanding of the underlying concepts and principles. This knowledge will enable them to effectively harness the power of AI and leverage its capabilities to enhance their workflows and decision-making processes [91].

Concepts such as machine learning (ML) and deep learning (DL) are fundamental components of AI that enable systems to learn from data and make predictions or decisions without being explicitly programmed. In the AEC context, ML and DL can be applied to various tasks, such as building energy analysis, structural optimization, and construction site monitoring [91]. Natural language processing (NLP) is a branch of AI that deals with the interaction between computers and human language [109]. In the AEC industry, NLP can be utilized for tasks such as interpreting construction documents, processing requests for information (RFIs), and facilitating communication between project stakeholders.

For instance, the popular generative design concept is an AI-driven approach that leverages computational power to explore a vast design space and generate multiple design alternatives based on predefined constraints and objectives [110]. This technique has the potential to revolutionize the design process in the AEC industry by enabling architects and engineers to explore a broader range of design solutions and optimize their designs for various performance criteria [111].

By understanding these core AI concepts, AEC professionals can better recognize the potential applications of AI within their domain and make informed decisions about AI adoption [108]. For instance, they can identify opportunities for automating repetitive tasks, optimizing design processes, and enhancing collaboration among project stakeholders [91]. Additionally, this knowledge can help professionals navigate the challenges associated with AI implementation, such as data quality, model interpretability, and ethical considerations.

6.2. Proficiency in AI Tools

Familiarity with AI tools and platforms is crucial for AEC professionals. Tools such as TensorFlow, PyTorch, and OpenAI's GPT-4 enable the development and customization of AI models tailored to specific AEC applications [112–115]. Professionals should be adept at using these tools to implement AI-driven solutions that enhance design, planning, and operational efficiency. AEC professionals can leverage AI applications such as generative design, computer vision-based construction site monitoring, and natural language processing for document analysis.

For example, OpenAI's GPT-4 is a state-of-the-art language model that has demonstrated remarkable capabilities in natural language processing tasks [114]. In the AEC industry, GPT-4 can be utilized for tasks such as interpreting construction documents, processing requests for information (RFIs), and facilitating communication between project stakeholders. By being proficient in these AI tools and platforms, AEC professionals can develop and deploy customized AI solutions that address specific challenges within their domain. They can create AI models for optimizing building designs based on energy efficiency, structural integrity, and material usage [111]. Additionally, they can leverage AI for predictive project management, construction site optimization, and data-driven decision-making throughout the AEC process [91].

Furthermore, familiarity with these tools enables AEC professionals to stay up to date with the latest advancements in AI and adapt their workflows accordingly. As AI technologies continue to evolve, professionals who are well-versed in these tools will be better equipped to integrate new AI capabilities into their practices, driving innovation and efficiency within the industry.

6.3. Data Management for AI Applications

Effective AI applications in AEC require robust data management skills. AEC professionals must be proficient in data collection, preprocessing, and management techniques [115]. They need to ensure the quality of data, work with large datasets, and use this data to train AI models accurately. Understanding data privacy and security considerations is also essential [116].

Data is the foundation of any AI system, and its quality and management significantly impact the performance and reliability of AI models [115]. In the AEC industry, data can come from various sources, such as Building Information Modeling (BIM) systems, sensor networks, and project documentation [91]. AEC professionals must be skilled in collecting, cleaning, and preprocessing this data to ensure its suitability for training AI models.

Effective data management involves techniques such as data cleaning, feature engineering, and data augmentation. Data cleaning involves identifying and handling missing or inconsistent data, while feature engineering involves selecting and transforming relevant features from the data to improve model performance. Data augmentation techniques, such as image manipulation or synthetic data generation, can be used to increase the size and diversity of training datasets, enhancing the robustness of AI models.

Handling large datasets is another critical aspect of data management in the AEC industry. Construction projects often generate vast amounts of data, and AI models must process and analyze these large datasets efficiently [91]. AEC professionals should be familiar with techniques for distributed data processing, parallel computing, and cloud-based data storage and management solutions. Furthermore, data privacy and security considerations are paramount in the AEC industry, where sensitive information related to projects, clients, and stakeholders is involved [116]. AEC professionals must understand data protection regulations, implement appropriate security measures, and ensure the ethical and responsible use of data in AI applications. By developing strong data management skills, AEC professionals can ensure the quality and integrity of the data used with AI models, leading to more accurate and reliable AI-driven solutions. This can enhance decision-making processes, optimize workflows, and drive innovation within the industry.

6.4. Programming and Software Development

Proficiency in programming languages and software development is necessary for developing and integrating AI applications. These programming languages such as Python [117] and C-Sharp [118] are widely used in AI and machine learning projects, and software development, enabling professionals to create, modify, and optimize AI algorithms and models. Python [117], for example, has become a popular choice due to its rich libraries, frameworks and support for AI development. C-Sharp, on the other hand, supports the development of desktop and web applications which can be used with AI systems. Likewise, the use of Python and C-Sharp for Application Programming Interface (API) development and integration allows AEC professionals to connect AI tools with existing software solutions, such as Building Information Modeling (BIM) platforms. This capability is essential for creating seamless workflows and enhancing interoperability between different software systems. By developing APIs, professionals can enable communication and data exchange between AI models and other software applications, facilitating the integration of AI capabilities into existing AEC workflows.

Understanding the software development process, including version control, testing, and deployment, is critical for creating robust and reliable AI applications. Additionally, knowledge of deployment strategies, such as containerization and cloud deployment, is essential for ensuring the successful and efficient deployment of AI solutions in production environments. Design patterns provide reusable solutions to common software design problems, promoting code reusability, flexibility, and scalability, which are essential for AI applications that may need to evolve and adapt over time. By combining programming skills, API development knowledge, software development lifecycle practices, and software design principles, AEC professionals can effectively develop, integrate, and maintain AI solutions that seamlessly integrate with existing systems and workflows, ultimately enhancing productivity, efficiency, and innovation within the industry.

6.5. Design Thinking and Creativity

Integrating AI into the AEC industry requires a combination of technical expertise and creative problem-solving skills. By leveraging generative design techniques, professionals can explore a broader range of design alternatives and optimize solutions based on various performance criteria, such as energy efficiency, structural integrity, and material usage [111,119]. Adopting a design thinking mindset can help professionals identify opportunities for AI applications, understand user needs, and develop innovative solutions that address real-world challenges in the AEC industry. The use of generative AI in the AEC industry can foster a more collaborative and iterative design process, enabling professionals from different disciplines to contribute their expertise and insights [111,119]. By leveraging AI-driven tools and design thinking methodologies, AEC professionals can enhance their creativity, explore unconventional solutions, and drive innovation within the industry [110]. Design thinking methodologies emphasize user-centered design, iterative prototyping, and collaborative problem-solving, which can be applied to the development and implementation of AI solutions in the AEC industry [120]. These methodologies encourage professionals to work with stakeholders, to define their needs, ideate potential solutions, prototype and test concepts, and continuously refine and improve the solutions [121].

Furthermore, the integration of AI and generative design can facilitate a more efficient and data-driven design process, enabling professionals to rapidly explore and evaluate a vast number of design alternatives [111,119]. By combining AI-driven optimization algorithms with human creativity and domain expertise, AEC professionals can identify innovative solutions that balance multiple design objectives and constraints, such as cost, sustainability, and user experience [91,110].

Ultimately, the successful integration of AI in the AEC industry requires a synergy between technical proficiency, creative problem-solving skills, and a design thinking mindset. By embracing these elements, professionals can leverage the power of AI to enhance collaboration, drive innovation, and deliver more efficient and sustainable solutions for the built environment.

6.6. Developing Skills and Competencies

6.6.1. Formal Education and Certification Programs

Formal education and certification programs play a crucial role in equipping AEC professionals with the necessary knowledge and skills to effectively integrate AI into their workflows. University courses can provide a solid foundation in AI concepts, machine learning algorithms, data science techniques, and their applications in the AEC domain [91]. By offering specialized courses and interdisciplinary programs, universities can bridge the gap between different disciplines and foster collaboration between architects, engineers, and computer scientists [119].

Similarly, professional certifications can also equip professionals with the required expertise and commitment to adopt and integrate AI into their workflows. Certifications from reputable organizations like Coursera and edX can demonstrate proficiency in areas such as project management, data science, and AI. These certifications can enhance the credibility and competitiveness of AEC professionals, signaling their ability to effectively integrate AI solutions into their projects. Formal education and certification programs can provide a structured learning path for professionals, ensuring they acquire the necessary theoretical and practical knowledge to navigate the complexities of AI implementation in the AEC industry. These programs can cover topics such as data management, programming, software development, and design thinking, enabling professionals to develop a well-rounded skillset [91,108]. By investing in formal education and certification programs, AEC professionals can stay ahead of the curve and position themselves as leaders in the integration of AI technologies within their industry. This commitment to continuous learning and professional development can drive innovation, enhance project outcomes, and contribute to the overall advancement of the AEC sector.

6.6.2. Industry Training and Workshops

Industry training and workshops play a vital role in equipping AEC professionals with the practical skills and knowledge required to effectively integrate AI into their workflows. Workshops and seminars organized by industry associations and professional bodies, such as the American Institute of Architects (AIA) and the Construction Management Association of America (CMAA), can provide targeted training sessions on AI integration in the AEC domain [108]. These events offer hands-on experiences, case studies, and best practices shared by industry experts, enabling professionals to learn from real-world examples and gain practical insights.

Online courses and tutorials offered by platforms like Coursera [122], edX [123], and Udacity [124] can complement industry training by providing flexible learning opportunities for professionals [91]. These online resources often cover a wide range of topics related to AI applications in the AEC industry, including data management, programming, software development, and design thinking. The self-paced nature of these courses allows professionals to balance their learning with work commitments, making it easier to acquire new skills and stay up to date with the latest advancements in AI technologies.

In addition to workshops and online courses, industry training can also take the form of mentorship programs or on-the-job training initiatives. Experienced professionals who have successfully integrated AI into their workflows can share their knowledge and provide guidance to those seeking to adopt these technologies [108]. This hands-on approach can accelerate the learning curve and facilitate the effective implementation of AI solutions within AEC projects. By bringing together diverse perspectives and expertise, these training opportunities can promote interdisciplinary collaboration and facilitate the development of innovative AI-driven solutions tailored to the unique challenges of the AEC industry.

6.6.3. On-the-Job Training and Mentorship

Having on-the-job training and mentorship programs can offer a hands-on approach to developing the skills and knowledge required for integrating AI into AEC workflows. Mentorship programs in which less experienced professionals are paired with mentors who have expertise in AI and generative design can facilitate knowledge transfer and skill development [108]. Mentors can provide guidance, share practical insights, and help mentees navigate the complexities of AI integration, ensuring a smoother transition and adoption of these technologies. Also, project-based learning is another effective approach to on-the-job training. By engaging in real-world projects that involve AI integration, professionals can gain practical experience and reinforce their learning [91,119]. This hands-on approach allows them to apply theoretical knowledge to actual AEC challenges, fostering a deeper understanding of AI applications and their impact on project outcomes. Through project-based learning, professionals can develop problem-solving skills, collaborate with cross-functional teams, and gain insights into the practical considerations and challenges associated with AI implementation. On-the-job training and mentorship programs can also foster a culture of continuous learning and knowledge-sharing within organizations. By encouraging experienced professionals to share their expertise and mentor others, organizations can create a supportive environment that promotes professional growth and facilitates the effective adoption of AI technologies [119]. These programs can help organizations identify and address skill gaps, enabling them to develop targeted training initiatives and allocate resources effectively. By investing in on-the-job training and mentorship, organizations can build a workforce that is well-equipped to leverage AI technologies, driving innovation and enhancing project outcomes within the AEC industry [91,111].

7. Conclusions

The application of AI using large language models (LLMs) to automate the design creation process requires a profound change in the way all professions related to the built environment think and operate. The AEC industry has been a relatively late adopter of AI compared to most other industries, and its applications have been mainly in construction, more rarely in architecture and virtually not at all in engineering. Notably, in the architecture, engineering, and construction (AEC) business domain, applied artificial intelligence, in general, and generative AI technologies and large language models, in particular, are gaining intense practical interest. Largely, AEC suffers from productivity issues and is yet to fully reap the benefits of automation, unlike other sector industries. As a result, increasingly, sector professionals are collaborating with digital technology experts on viable data-driven automation solutions to improve AEC business processes, implicating models of collaboration. The use of systems thinking guidelines is identified as a very important imperative to implement useful solutions effectively. These automation challenges are particularly relevant in the broader context of the advancement of smart sustainable cities and built environments—their design, construction, operation, and transformation. The AEC industry has been a relatively late adopter of AI compared to most other industries, and its applications have been mainly in construction, more rarely in architecture and virtually not at all in engineering. The integration of generative AI in architecture, engineering, and construction (AEC) presents transformative opportunities and significant challenges. RoboGPT's use of ChatGPT-4 for automated sequence planning in construction tasks and the application of GPT-3.5 for enhancing highway construction safety analysis illustrate the potential for AI to optimize processes and improve safety outcomes. The selection of sustainable materials and the integration of AI with Building Information Modeling (BIM) demonstrate AI's role in promoting environmentally responsible construction practices. Generative AI also offers substantial benefits during the pre-construction phase by synthesizing feasibility reports, streamlining decision-making, and ensuring compliance with regulations. During construction, AI enhances progress monitoring, resource optimization, and team communication, contributing to efficiency and sustainability. Post-construction, AI supports the creation of detailed documentation, ensuring the building's long-term performance. Despite these advantages, the adoption of generative AI in AEC is not without challenges. Ethical concerns related to data privacy, bias, and accountability must be addressed. The need for significant investment in technology infrastructure and training, along with issues of data security and the complexity of capturing extensive domain knowledge, pose additional hurdles. The AEC sector has experienced substantial transformations driven by the integration of advanced technologies such as AI, big data analytics, IoT, and cloud computing. These innovations are reshaping the educational landscape and addressing the evolving needs of 21st-century learning. AI, in particular, has emerged as a powerful tool in both education and construction, offering personalized learning experiences and optimizing various AEC processes. A limitation of this study is the exclusion of professional design publications that specifically address the contributions of generative AI to the built environment. This gap may limit the comprehensiveness of the literature review, particularly in capturing industry-specific insights and applications. Also, a wide range of methods could be considered for use with archival publications, including case studies, surveys, and others. This will ensure sufficient statistical data from primary reports in certain topical areas, which would allow for a subordinate meta-analysis. Incorporating a supporting quantitative analysis could enhance future research.

In education, AI's ability to analyze large datasets and provide tailored learning paths has revolutionized teaching and administrative functions. By customizing content to meet individual student needs, AI enhances learning efficiency and accessibility, making higher education more attainable for diverse student populations. AI-driven tools, such as chatbots, further support personalized learning and adaptive systems, significantly improving educational outcomes. In the construction industry, AI applications like GPT models enhance project management by identifying tasks, creating schedules, and offering insights during the pre-design phase. These technologies facilitate informed decision-making and provide instant training and feedback, crucial for engineering education and professional development. The integration of AI in AEC promotes the development of sustainable, intelligent, and durable infrastructure. To effectively harness AI's potential, AEC professionals must possess technical proficiency in AI concepts, programming skills, data management capabilities, and a creative, design-thinking approach. Formal education, certification programs, and industry training play vital roles in equipping professionals with the necessary skills. Additionally, on-the-job training and mentorship programs provide hands-on experience, fostering continuous learning and innovation. The integration of generative AI into AEC workflows requires a diverse set of skills and competencies. By focusing on technical proficiency, programming, design thinking, and ethical awareness, AEC professionals can effectively leverage these technologies to enhance project outcomes and drive innovation. Developing these skills through formal education, industry training, mentorship, and continuous learning is essential for ensuring that the AEC industry remains at the forefront of technological advancement. As AI continues to evolve, AEC professionals must be prepared to adapt and embrace new opportunities, ultimately transforming the way projects are designed, managed, and executed.

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