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# Generative Artificial Intelligence in Architecture, Engineering, Construction, and Operations: A Systematic Review

**Shoeb Ahmed Memon [1,*], Waled Shehata [1], Steve Rowlinson [1,2] and Riza Yosia Sunindijo [3]**

1 Faculty of Society and Design, Bond University, 14 University Drive, Robina, Gold Coast, QLD 4226, Australia
2 Department of Real Estate and Construction, Faculty of Architecture, the University of Hong Kong, Pokfulam, Hong Kong SAR, China
3 School of Built Environment, UNSW Sydney, Sydney, NSW 2052, Australia
* Correspondence: smemon@bond.edu.au

## Abstract

Generative artificial intelligence (GenAI) is a tool that can be applied to virtually all aspects of business and life, including the construction industry. However, the adoption of GenAI in the construction industry, as with other innovations, is slow, and many of its applications thus far have been rather simplistic or failed to deliver a useful, credible output. There is a limited understanding of how GenAI is adopted in current practice and its potential to improve future practice in architecture, engineering, construction, and operations (AECO). Using a systematic literature review approach, this study aims to map the current issues in applying GenAI. The literature review initially identified 1013 peer-reviewed articles from ProQuest, Scopus, and Web of Science. The articles were further filtered based on specific criteria, resulting in 28 articles being retained for thematic analysis. The findings show a cluster of patterns in which GenAI is being adopted and shows promise. The core themes identified are as follows: (1) project brief, (2) architectural design, (3) building information modelling, (4) structural design, (5) construction and demolition, (6) operations, and (7) urban governance. A typical trend noted in the AECO industry has been training AI models that achieve quicker results, improve quality, and use fewer resources.

**Keywords:** built environment; generative artificial intelligence; construction; AECO



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## 1. Introduction

Construction as an industry is notorious for its slow adoption of innovation. Despite using computer-aided technologies for many decades in different stages of the project lifecycle, the industry is still slow in implementing cutting-edge technologies and remains traditional in its ways of working. Coupled with a considerable increase in administrative requirements and expectations, the productivity of the industry suffers.

There has been an increased interest in artificial intelligence (AI), including GenAI, to improve processes in the workplace [1]. Organisations face a dilemma in either adopting a structured approach towards GenAI or other tools that elevate productivity. Part of the problem lies in how the construction industry is organised, unlike business models in other sectors, such as manufacturing, which make the most of digital technologies in lean production. Opportunities for the construction industry to follow suit are limited due to its project-based nature [2]. For instance, despite its advantages, building information modelling (BIM) has taken decades to integrate into the core business models of major construction organisations. The BIM maturity level in the construction industry is also still relatively low.

Explaining the attention given to GenAI's role in the construction industry, Hallo and Nguyen [3] postulate that its widespread use could lead to smart design and infrastructure, which promotes improvements and efficiency throughout the construction project lifecycle, from inception and design to bidding, financing, transportation, operation, and asset management [4].

Currently, the GenAI literature in the AECO sector is predominantly occupied with developing discipline-specific courses and how it could benefit education. Jelodar [5] highlighted applications in construction practice, especially in maintenance and training areas. Liao et al. [6] highlighted the improved effectiveness of building structural design through GenAI. Structural designs show promising outcomes when a finite element model is provided to ChatGPT [7]. Finite element modelling involves complex computational analysis for building design under various loading conditions [8]. It highlights the sophistication of GenAI models to understand and analyse complex designs. The research on the adoption of GenAI in the AECO sector is progressing but remains fragmented.

This study provides a comprehensive review of the GenAI in the AECO sector. There is a lack of understanding as to how GenAI is currently used in the sector and its potential to improve future practice. The objective of this paper is to identify patterns of GenAI applications in the AECO sector by performing a thematic review of the published literature in the field of study. The review specifically addresses the following research question: what are the current and future applications of GenAI in the AECO sector?

This paper is structured into four sections. Section 1 is an introduction to the study. Section 2 provides an overview of the related terms used in the database search and runs through the literature screening and data extraction methods. Section 3 focuses on the findings and patterns of themes and sub-themes of GenAI application. The discussion of the coverage of GenAI in AECO industries is presented in the same section, narrating the highlights from the literature. Section 4 presents the conclusions and limitations of the study. Section 5 presents future directions for research in this area.

## 2. Systematic Literature Review Process

As adopted from Moher et al. [9], a step-by-step approach was utilised to perform a systematic review to answer the research question on the adoption of GenAI in the AECO sector. The thematic literature review search process comprises four stages: (1) formulating search terms, (2) literature identification, (3) literature screening, and (4) data extraction. The detailed literature search process is shown in Figure 1. The automated Systematic Review Accelerator tool (SRA) was used to expedite the processes in this research—see Clark et al. [10].

### *2.1. Search Terms: GenAI, RIBA, and NATSPEC Plans of Work and Government Soft Landing*

To systematically develop the search query, key terms used in the AECO industry need to be considered. Several design process maps or plans of work are used worldwide to guide project stakeholders through the building's life cycle, including briefing, design, construction, handover, and operation and maintenance. In most countries, the process maps are set by the professional institutes or bodies and may have different names to indicate different stages or parts of stages. The Royal Institute of British Architects (RIBA), a global organisation driving excellence in the quality of the built environment, uses an eight-stage plan of work. More locally in Australia, National Building Specification (NATSPEC) developed a work plan to provide the project team with a road map for promoting consistency from one stage to the next, and to provide vital guidance to building projects [11]. NATSPEC's plan comprises seven stages, with some overlaps and similarities with RIBA. To avoid missing out on key stages, both terms used by the RIBA and NATSPEC plans of work were adopted.

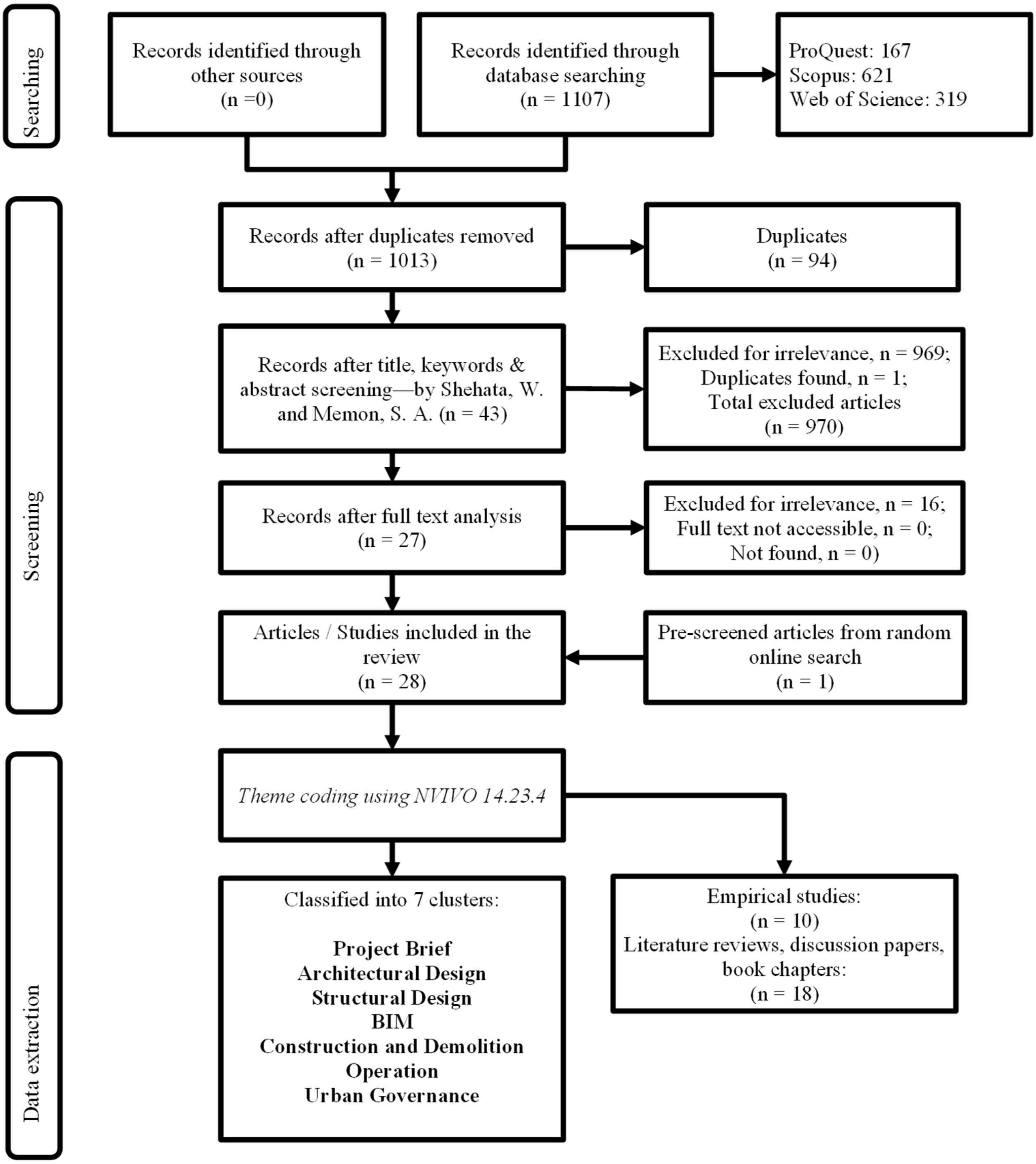


**Figure 1.** The procedure for selecting the final articles for thematic review.

While RIBA and NATSPEC plans of work set the stages of works, the role of digitalisation, particularly building information modelling (BIM), is pivotal for the construction industry, especially in the transition of information from one stage to another [12]. The literature identifies the potential for construction organisations to benefit from the integration of GenAI and BIM, such as in project planning [13], structural design [14], and cost planning and budgeting [15]. Therefore, searching the databases using BIM-specific terms in the AECO's work stages is essential. In addition, the UK Government Soft Landing (GSL) framework is also adopted to offer essential insights into key stages. GSL emphasises BIM in maintaining the "golden thread" of information throughout the facility's lifecycle [16]. GSL complements the existing plans of work used in the construction industry. GSL offers a smooth transition from construction to handover and project close out, and to facility operation, referred to as "soft landing". GSL drives a structured and consistent approach from the outset of a project to its delivery. Thus, the terms used by GSL complement the key terms used in RIBA and NATSPEC plans of work when exploring the use of GenAI in AECO (Table 1).

**Table 1.** Key terms used by RIBA and NATSPEC plans of work and the GSL framework. Adapted from RIBA [17] and Philp et al. [16] and respective AECO processes.

| | **Pre-Design** | | **Design** | | | | **Construction** | **Handover** | **In Use** | **End of Life** |
|---|---|---|---|---|---|---|---|---|---|---|
| **AECO** | Architecture and Engineering | | | | | | Construction | | Operations | NA |
| **RIBA (UK)** | 0<br>Strategic Definition | 1<br>Preparation and Brief | 2<br>Concept Design | NA | 3<br>Developed Design | 4<br>Technical Design | 5<br>Construction | 6<br>Handover and Closeout | 7<br>In Use | NA |
| **NATSPEC (Australia)** | NA | Establishment | Concept Design | Schematic Design | Design Development | Contract Documentation | Construction | NA | Facility Management | NA |
| **Government Soft Landing (UK)** | Initial Business Case | Final Business Case | NA | NA | NA | Design | Construction | Pre-Handover | Operational Stage | NA |

### *2.2. Literature Identification*

The cross-disciplinary databases on ProQuest, Science Direct, Scopus, and Web of Science were searched on 20 November 2024. The search range was set to start in 2018, which was when OpenAI created the first version of the Generative Pretrained Transformer (GPT) [18]. The publications retrieved from these four databases cover topics such as the practice or adoption of GenAI technologies.

Customised search strategies (Keywords) have been constructed following a consultation with Bond University's academic librarian to avoid missing key studies due to poorly constructed or improperly implemented searches. The search strategy comprises five main concepts: population (population within the AECO industry), variable (Technologies), scope (Plan of work according to RIBA, NATSPEC and GSL), region (Australia), and time range (2018–ongoing). The research string used in Scopus, ProQuest, and Web of Science is as follows:

(GenAI OR "Generative AI" OR "Generative artificial intelligence" OR ChatGPT OR "Generative Pretrained Transformer" OR LLM OR "Large language model") AND ALL = (Lifecycle OR "Life cycle" OR Life-cycle OR Architecture OR Engineering OR Construction OR Operation OR "Strategic definition" OR "Initial business case" OR "Preparation and briefing" OR Establishment OR "Final business case" OR "Concept design" OR "Schematic design" OR "Spatial coordination" OR "Technical design" OR "Design development" OR "Contract documentation" OR Design OR "Manufacturing and construction" OR Handover OR "Pre-handover" OR Use OR "Facility management" OR "Operational stage").

In Scopus and Web of Science, the initial search was refined to include only these document types: article, conference paper, review, book chapter, book, and editorial letters. In ProQuest, the initial search was refined to include only these source types: journal articles, conference papers and proceedings, theses, dissertations, and working papers. The study also would like to focus on the context of the Australian construction industry. However, due to a limited number of studies in this context, articles where at least one author was affiliated with an Australian institution were included instead. Table 2 presents a classification of articles and the scope of the existing review studies related to GenAI in AECO.

### 2.3. Literature Screening

The initial search results (n = 1107) were imported into the EndNote 21 software. The Deduplicator tool, part of the SRA, was used to find duplicates [19]. The resource list was checked for duplicates manually to minimise the risk of deleting unique references and ensure no duplicates were missed by the automatic checker. A total of 94 duplicates were deleted. Following their removal, the Screenatron tool on SRA was used to enable Shoeb and Waled to screen the work individually. Then, the Disputatron tool on SRA was used to automatically detect reviewer screening disagreements [10]. The title and abstract of the remaining 1013 records were reviewed for relevance to establish whether they are fit for full text review using SRA. The excluded articles primarily discuss GenAI in education and other irrelevant application fields. This extensive screening process eliminated 970 publications, resulting in 43 publications for further analysis.

Researchers undertook a preliminary full-text content analysis of the 43 articles and assessed them against the eligibility criteria. The primary criterion for qualifying was that the article must disclose an insight into the AECO industry's perspectives on GenAI. After the full text content analysis, 16 unrelated articles were removed, and 1 article was added from a general search over the internet by the research team based on relevance to the topic. In total, 28 articles were retained for analysis.

### 2.4. Data Extraction

The first layer of analysis of the 28 articles is presented in Table 2. It shows that many reviews and empirical investigations have been undertaken to explore the recent advancements in generative technologies. All 28 articles were examined in detail using NVIVO 14. The related GenAI applications in AECO were manually coded in the software, and relevant sections were extracted into the code. The patches of the literature were classified into one or more themes (codes or clusters) using thematic analysis procedures proposed by Clarke & Braun [20]. Thematic analysis provides a comprehensive approach to identify iteratively refining codes and their relationships in relation to GenAI in the AECO sector. It involves a cyclical process of coding, analysing, and then recoding based on the emerging insights and patterns within the data. This method deepens data understanding and ensures that the reported coding scheme is comprehensive and accurate.

A total of seven themes were identified from the 28 articles: (1) project brief, (2) architectural design, (3) structural design, (4) BIM, (5) construction and demolition, (6) operations, and (7) urban governance. Under each theme, sub-theme levels are identified. Each article is classified under one or more of the seven identified themes as presented in Table 2. It has been argued in the introduction that GenAI use has been fragmented and does not present an organised approach in the construction sector. This is why the results present GenAI in different domains of the sector. Each theme identified presented a number of coded statements from the literature, which suggests importance and application. Figure 2 graphically presents the thematic hierarchy chart of the seven themes and sub-level themes based on the number of statements to support the themes. The sub-themes of each core theme are displayed in Figures 3–9 in relevant sections.

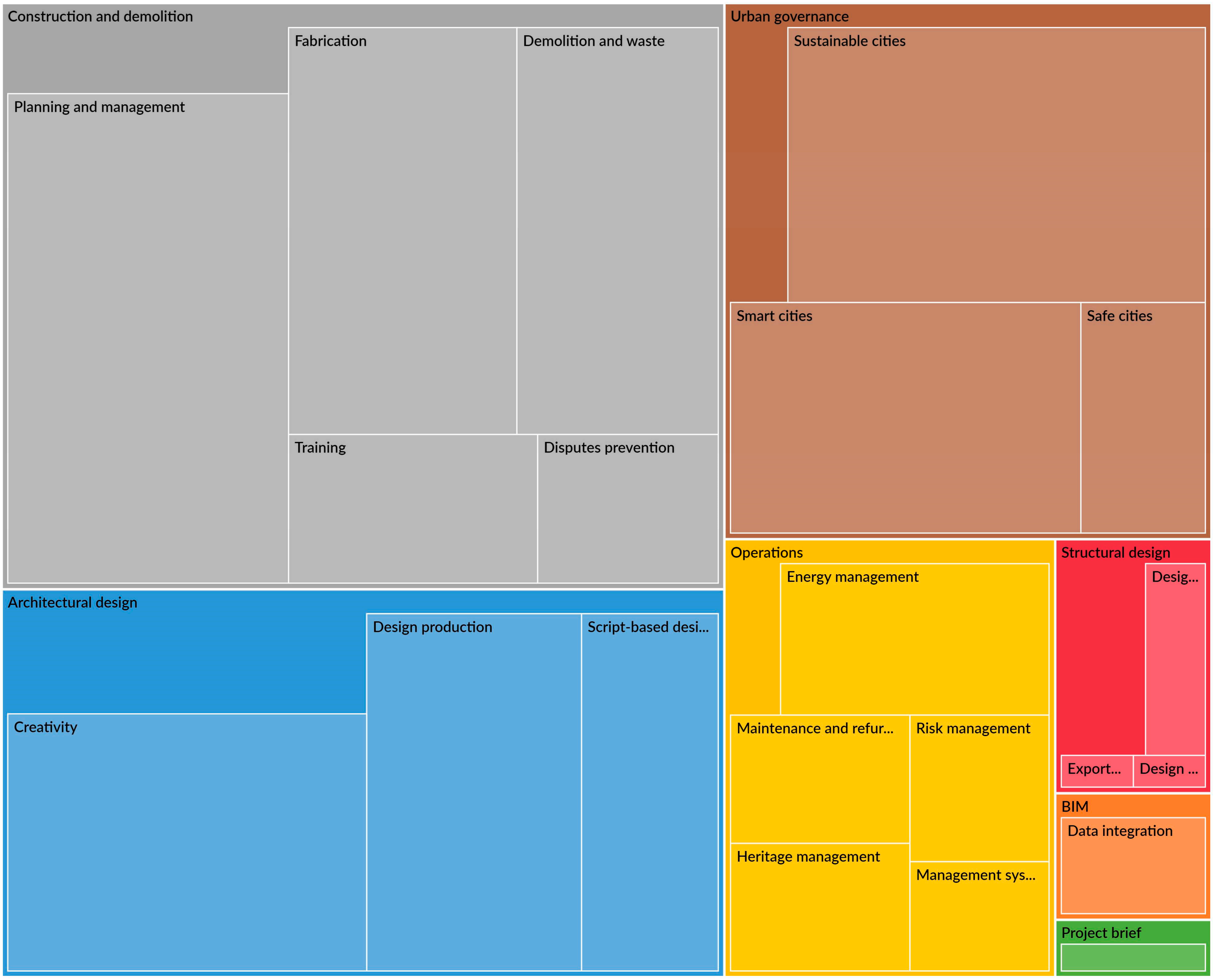


**Figure 2.** Thematic hierarchy chart based on coding in NVIVO 14.

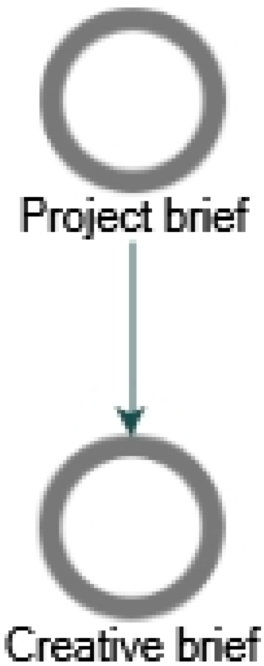


**Figure 3.** Strategic definition and brief thematic tree.

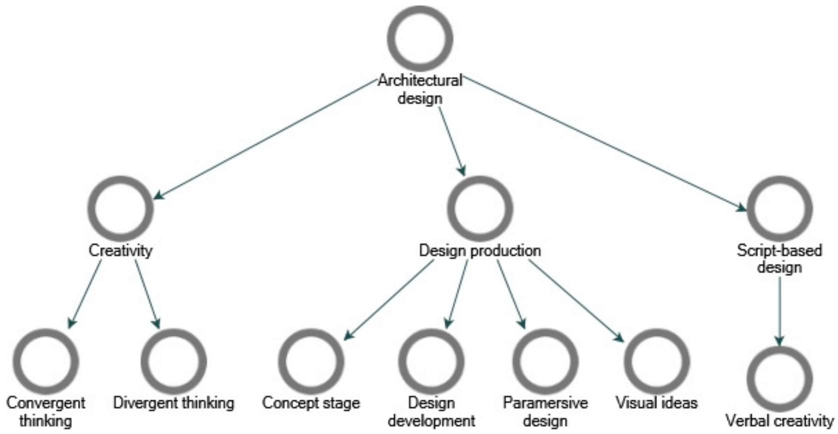


**Figure 4.** Architectural design thematic tree.

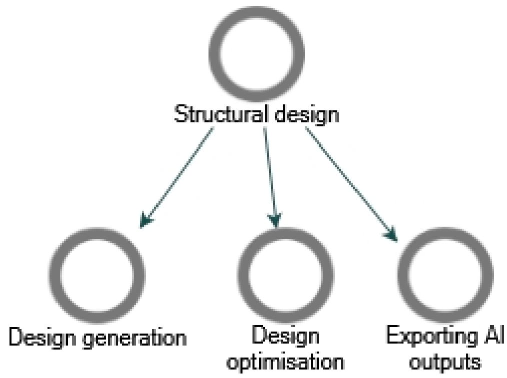


**Figure 5.** Structural design thematic tree.

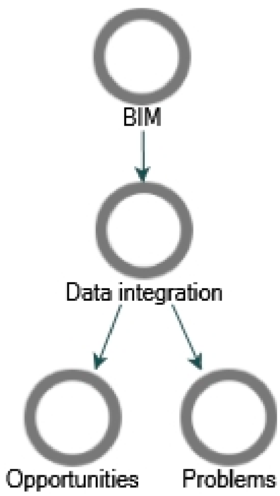


**Figure 6.** BIM thematic tree.

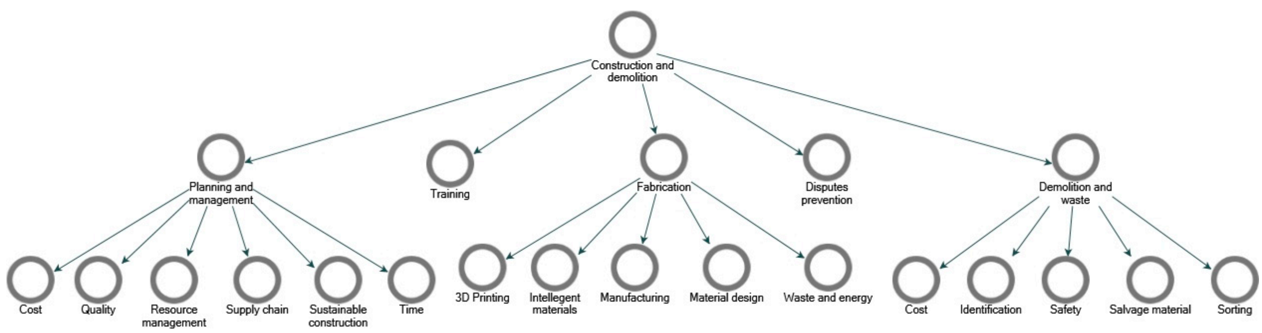


**Figure 7.** Construction and demolition thematic tree.

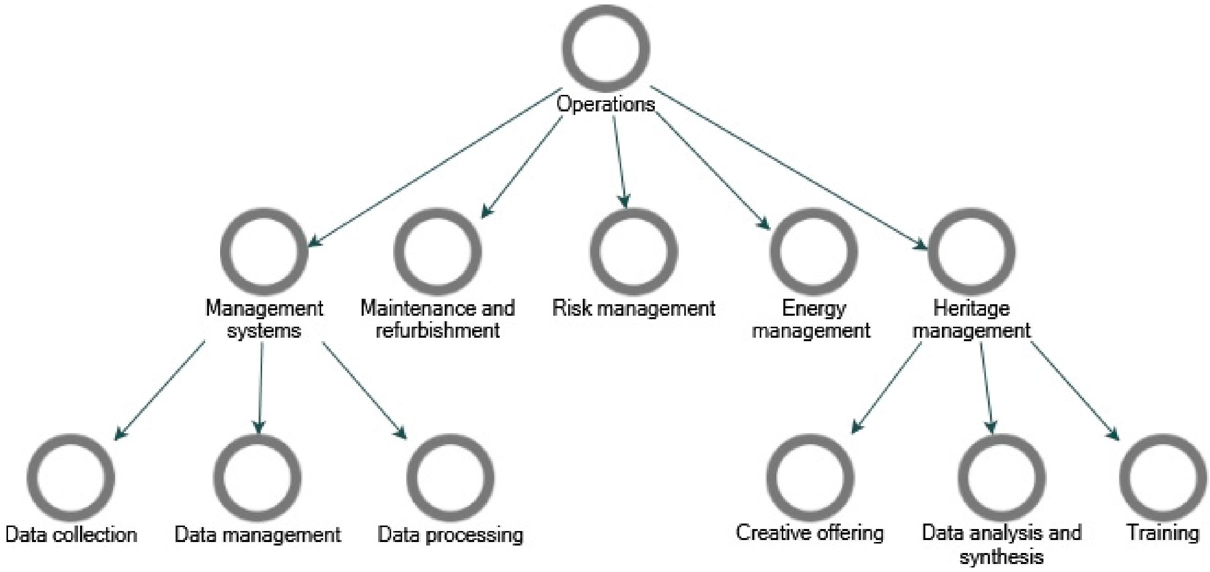


**Figure 8.** Operations thematic tree.

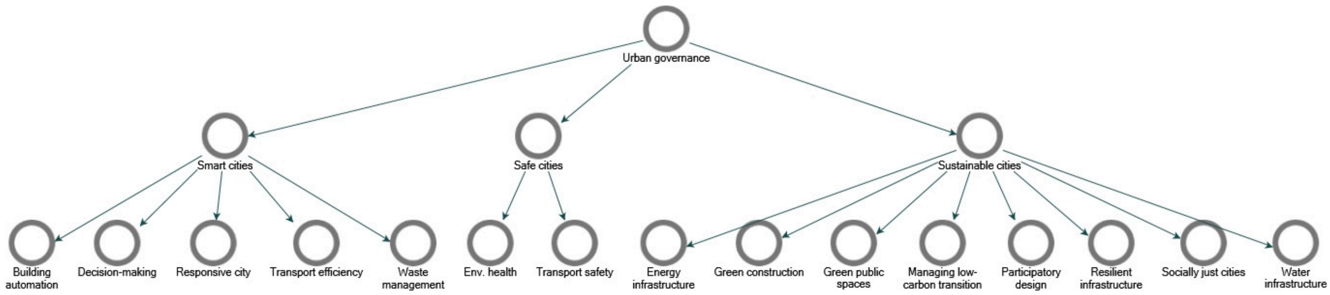


**Figure 9.** Urban governance thematic tree.

**Table 2.** Classification of articles and scope of existing review studies related to GenAI in AECO.

| | | Classification of Articles | | | | Scope of Existing Studies Related to GenAI | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Review/Opinion | Empirical Investigation | Case Specific to Australia | Project Brief | Architectural Design | Structural Design | Building Information Modelling | Construction and Demolition | Operations | Urban Governance |
| 1 | Alahi et al. [21] | ✓ | | | | | | | | ✓ | ✓ |
| 2 | Chen et al. [22] | | ✓ | ✓ | | | | | ✓ | | |
| 3 | Cheng et al. [23] | ✓ | | | | | | | | | ✓ |
| 4 | Cugurullo et al. [24] | ✓ | | | | | | | | ✓ | ✓ |
| 5 | De Silva et al. [25] | | ✓ | ✓ | | | | | | | ✓ |
| 6 | Dodampegama et al. [26] | ✓ | | | | | | | ✓ | | |
| 7 | Drogemuller et al. [27] | ✓ | | ✓ | | ✓ | | | | | |
| 8 | Du et al. [28] | ✓ | | | | | | ✓ | ✓ | ✓ | |
| 9 | Fan et al. [29] | ✓ | | | | | | | ✓ | ✓ | ✓ |
| 10 | Gerber [30] | ✓ | | ✓ | | | | | ✓ | | |
| 11 | Haris et al. [4] | ✓ | | | | ✓ | | | ✓ | ✓ | ✓ |
| 12 | Le Nguyen et al. [31] | | ✓ | | | | | | ✓ | | |
| 13 | Matharaarachchi et al. [32] | | ✓ | ✓ | | | | | | | ✓ |
| 14 | Ohueri et al. [33] | ✓ | | | | | | | ✓ | | |
| 15 | Oviedo-Trespalacios et al. [34] | | ✓ | | | | | | ✓ | | |
| 16 | Perin [35] | ✓ | | | | ✓ | | | | | |
| 17 | Qin et al. [36] | | ✓ | | | | ✓ | | | | |
| 18 | Rafizadeh et al. [37] | ✓ | | | | ✓ | ✓ | ✓ | ✓ | ✓ | |

**Table 2.** *Cont.*

| | | Classification of Articles | | | Scope of Existing Studies Related to GenAI | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Review/Opinion | Empirical Investigation | Case Specific to Australia | Project Brief | Architectural Design | Structural Design | Building Information Modelling | Construction and Demolition | Operations | Urban Governance |
| 19 | Regona et al. [38] | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| 20 | Reja et al., [39] | ✓ | | | | | | ✓ | ✓ | ✓ | |
| 21 | Saad et al. [40] | ✓ | | | | | | | ✓ | ✓ | |
| 22 | Shishehgarkhaneh et al. [41] | | ✓ | ✓ | | | | | ✓ | | |
| 23 | Spennemann [42] | ✓ | | | | | | | | ✓ | |
| 24 | Tan and Luhrs [43] | | ✓ | ✓ | ✓ | ✓ | | | ✓ | | |
| 25 | Wahba et al. [44] | ✓ | | | | | | | | ✓ | |
| 26 | Wang et al. [45] | ✓ | | | | | | | ✓ | | ✓ |
| 27 | Wang et al. [46] | | ✓ | | | | | | ✓ | | |
| 28 | Yazdi et al. [47] | | ✓ | ✓ | | | | | ✓ | ✓ | |

## 3. Analysis and Discussion

The following is the synthesis of relevant applications of GenAI in the seven identified literature themes pertinent to the AECO industry.

### *3.1. Project Brief*

Figure 3 presents a thematic tree for the project brief, highlighting the role of GenAI in developing project briefs. GenAI has shown promising results in the early stages of a project's lifecycle—strategic definition and project brief stage. The design research on the effectiveness of GenAI in supporting architects by Tan and Luhrs [43] concluded that GenAI shows an encouraging potential for developing project briefs. In the early project brief stage, architects often rely on the client to clarify needs and expectations about the project and their experience of working in the field. This convergent thinking process, coupled with information about projects in GenAI, assists in producing realistic and creative project briefs. This kind of tool offers architects alternative design and rendering options that are creative and time-efficient [43].

Despite improved focus on sustainability in the design and execution phase of projects, it is argued that sustainable development goals (SDGs) could be better achieved when considered at a briefing stage, paving the way for design and execution that is well linked to sustainability outcomes. Regona et al. [38] identified the role of machine learning models in brief development, which are targeted towards sustainable development goals—generating competitive, economically viable briefs, and improving project focus on sustainability [48].

### *3.2. Architectural Design*

Figure 4 presents a thematic tree for architectural design, highlighting the role of GenAI in producing creative, quicker, and script-based designs. GenAI tools, such as Midjourney and Xcool, generate images based on users' exploratory thinking and a set of keywords acting as scripts for design proposals. Generated imagery provides a cohesive overarching design idea that is used for a design project and forms the basis for successive design stages, creatively and accurately [49,50]. Based on the project brief, GenAI tools offer schematic drawings and useful ideas for elevations to be used for comprehensive architectural designs. The availability of alternative design options based on the project brief and evolving clients' expectations also assists in sound decisions for projects. This provides an opportunity for architects to explore divergent and creative architectural designs. Marrone et al. [51] emphasise the collaboration between GenAI and humans to promote creativity and reduce the time it takes to produce creative designs. Rafizadeh et al. [37] and Wang et al. [45] find that automation using GenAI in architecture, engineering, and construction promises improved design productivity, creativity, safety, and overall quality. Architectural form and 3D models are often generated in tools like SketchUp and Revit when developing initial design. Having the opportunity to visualise multiple architectural forms in virtual space could potentially benefit design decisions.

Drogemuller et al. [27] used GenAI in conjunction with virtual reality technology to develop architectural designs, particularly architectural form generation, in a seamless process compared to the traditional design process. They tested versioning, iteration, mass customisation, and continuous differentiation in two small case studies to produce progressively more complex architectural forms.

It is also crucial to recognise the issues related to the use of GenAI. Information generated by GenAI tools may lack project context, which could result in poor decisions. Creative text-to-image GenAI tools may overlook other crucial design considerations, such as functionality, economic sustainability, and technical feasibility [37]. There is also a growing concern about the protection of sensitive project information and intellectual property rights with the increased use of GenAI in the design process [37] and the architectural design as a product [35]. According to Perin [35], images generated by AI as architectural designs refer to historically defined architectural elements, which defies the purpose of creativity and progress in architectural design practice. While encouraging the interrogation of the algorithms used by GenAI in the architectural design productions, Perin is sceptical about the positive contribution GenAI can bring to the professional design practice, not only when compared to the traditional architectural design processes, but also when compared to the pre-BIM computer-aided design presentation tools. Wang et al. [45] identify ethical challenges, such as data fraud and privacy disclosure, as the main obstacles to realising the SDGs using GenAI.

### *3.3. Structural Design*

Figure 5 presents a structural design thematic tree, and the literature points to the role of GenAI in structural design generation, optimisation, and exporting outputs. The literature points to improved results of structural design when GenAI tools are provided with technical specifications about the design [7]. For example, Qin et al. [36] produced a shear wall system design using a large language model (LLM) and GenAI in structural design. In their research, the shear wall design was generated and optimised in an iterative process, ensuring structural safety and cost-effectiveness, significantly reducing the design outcome's material consumption and improving the design efficiency. Liao et al. [14] identified the role of GenAI in design optimisation by learning from existing structural designs. Qin et al. [36] postulated a two-stage design optimisation method based on rules, such as material consumption and performance criteria. They pointed out that the design can be exported to computer-aided design tools for subsequent modification, analysis, and verification. Rafizadeh et al. [37] also briefly mentioned the role of GenAI in structural design optimisation. The potential for GenAI tools in the structural design process heavily relies on the specific type of tool and the technical design specification offered.

### *3.4. Building Information Modelling*

Figure 6 presents a thematic tree for building information modelling (BIM), where opportunities and obstacles for GenAI in data integration have been identified. BIM has shown promising results, with a volume of research on BIM integration with other Industry 4.0 technologies in AECO. However, the potential for GenAI together with Industry 4.0 is rarely discussed. Du et al. [28] prepared a literature review exploring the relationships between BIM and GenAI in the construction industry. They find that the ease of data integration and conversion between BIM and GenAI tools is still in the early stages of development [28]. Part of the reason is that the compatibility of data and proprietary information is not always available to GenAI tools since most of the GenAI tools are not trained on BIM information and rely on open-source data. There is an opportunity for construction organisations to train and adapt the GenAI tool available with commercial vendors to suit specific business needs. This would essentially allow professionals to develop, update, and analyse BIM models while adhering to professional codes and practices.

In a part of their research on digital twins (DT), Reja et al. [39] discussed the vast opportunities of DT to exchange geometric data to and from BIM. DT systems become a reality when IoT devices, actuators, and sensors connect to BIM models, which can live-transmit their readings to DT models. Information includes temperature, pressure, and performance metrics, among others. This capability further empowers the possibilities of BIM at different project stages to observe progress, simulate scenarios, and enable stakeholders to analyse ground-collected information details live on digital models, all while being physically distant from the site. This is also linked to Section 3.5. Construction and Demolition theme; when the live information is sent to DT, it enables remote site monitoring and progress reporting.

### *3.5. Construction and Demolition*

Figure 7 presents a thematic tree for construction and demolition, highlighting the role of GenAI in planning and management, fabrication, demolition, waste, dispute prevention, and training. GenAI generates future scenarios (for example, risk assessments) that help construction and site managers anticipate and respond to upcoming opportunities and problems, enabling sound decisions (risk mitigation). LLMS such as GPT-3 have been shown to allow for intuitive interactions and communication between project stakeholders and the DT of construction sites. Producing human-like text, LLMs facilitate information analysis, interpretation, and scenario propositions, which enables informed decision-making [39]. Inherent in their development mechanisms, LLMs continuously learn and improve, which may contribute to further confidence in case-specific contexts and/or non-traditional scenarios. This strategic thinking is cost- and time-effective compared to traditional risk management methods, which heavily rely on the professional judgement of individuals [52].

GenAI has the potential to completely transform traditional construction practices by drastically reducing material waste and expediting the construction schedule [4]. Material waste in projects is often neglected and considered an unintended consequence of industry practices. When material waste management is prioritised using GenAI, it could offer an analysis of existing resource allocation and the best course of action in given circumstances, leading to better management in accordance with the project schedule [4].

Saad et al. [40] emphasised the role of GenAI in revolutionising materials in the building industry. They argued that GenAI has tremendous potential, from creating more durable substances to improving their performance, sustainability, and efficiency. GenAI opens up transformative fabrication possibilities that fundamentally alter how components are designed, manufactured, and assembled [4]. GenAI technologies have extended to quality control in steel fabrication processes, contributing to notable advancements in the industry. For example, Civimec, an Australian fabrication company, have embraced AI-based computer vision systems to enhance quality control measures by detecting defects and deviations in steel components.

Le Nguyen et al. [31] used optimisation methodologies in GenAI and machine learning (ML) to discover new concrete mixture designs that enhance strength and cost-efficiency, and reduce embodied $CO_2$. The mix designs generated by the framework were successfully validated through experimental tests, corroborating the predictive outcomes. The results of their research led to the development of an open-access web application that enables construction industry stakeholders to optimise concrete mixture designs. Similarly, Wang et al. [46] used GenAI to optimise engineered cementitious additives to enhance concrete strength properties.

From design to off-site fabrication and site works, construction processes can be optimised by leveraging machine learning algorithms, computer vision, and advanced robotics [4]. Optimisation covers reducing greenhouse gas emissions, resources, waste, and assembly times while increasing quality. On-site assembly and installation with GenAI assistance is witnessing a paradigm shift, as it reduces labour, avoids human errors, and enhances rates of productivity and sustainability. Generating accurate descriptions would enable informed decision-making in infrastructure operations and safety. Ohueri et al. [33] and Dodampegama et al. [26] found that robots equipped with GenAI have the potential to process and interpret real-time data during building construction and demolition to sort waste into reusable, recyclable, and non-recyclable materials. Ohueri et al. [33] focused on the human–robot collaboration opportunities for training construction waste identification sensors. However, Dodampegama et al. [26] found that existing GenAI tools still lag in human–robot collaboration, especially with no publicly available construction and demolition waste datasets to progress AI in real-life waste sorting tasks. Ohueri et al. [33] and Haris et al. [4] also expressed ethical and safety concerns that may result from the overreliance on robots in this field.

Shishehgarkhaneh et al. [41] found that the integration of advanced transformer-based model technologies (such as BERT, RoBERTa, and ELECTRA) in the construction sector enhances its ability to navigate international market dynamics. This would enable more resilient and responsive supply chain operations through timely risk identification and proactive management strategies. Wang et al. [45] and Regona et al. [38] found that ChatGPT contributes to training workers for complex engineering projects. The implementation of AI in construction management enhances safety, speed, accuracy, and efficiency of operations.

Training has become an important application of GenAI. Whether the training is for safety [22] or company policy [4], GenAI tools can prepare appropriate materials and information in a structured manner to autonomously deliver induction sessions. These materials can be adapted to best suit the training objective, including but not limited to engaging, illustrative, and assessment-based content. Chen et al. [22] investigated the use of deep learning applications to boost situational safety awareness and work efficiency for on-site workers and managers. Their research incorporated a simulation using augmented reality glasses on a construction site, which, despite the promising results, showed serious limitations such as obstructing users' field of view, causing distractions and fatigue resulting from long periods of use, and compromising focus on construction work tasks. While Yazdi et al. [47] found that GenAI has revolutionised risk assessment by providing quick, comprehensive, and pertinent evaluations, they recognised GenAI's shortfalls and gaps compared to human precision and contextual understanding in both construction sites and building operations. For instance, GenAI's hazard identification accuracy and the practicality of its generated measures need refinement for buildings in operation. In an alarming finding, GenAI's risk control measures are broad and found not to align with statutory safety legislation. Overall, Yazdi et al. [47] acknowledged GenAI's strengths in relevance and response times while highlighting areas such as accuracy, practicality, credibility, clarity, and comprehensiveness where it could improve. AI demonstrates a reasonable level of contextual understanding, although it may excel in this area by learning.

Concerning safety while operating heavy machinery, ChatGPT provides responses that are consistent with evidence-based guidelines in developed countries but are oversimplified. Oviedo-Trespalacios et al. [34] found that while ChatGPT correctly provided advice on mitigating fatigue for those operating heavy machinery, the advice would only have benefited if it were followed in its entirety. If the operator decides to pick and choose which recommendation(s), they may end up with an intervention that leads to an inappropriate (insufficient) response to overcome fatigue safely. The research finds that information generated by GenAI tools on various safety topics may be limited, oversimplified, and mostly untraceable from reliable sources.

While Gerber [30] recognised some of the powerful GenAI tools that can assist judges in drafting judgements, recalling procedural orders, and deciding construction dispute cases, GenAI cannot replace judges. GenAI still requires close supervision and close monitoring of the system.

### *3.6. Operations*

Figure 8 presents a thematic tree for operations. In building operations, Yazdi et al. [47] found that GenAI has revolutionised risk management by providing quick, comprehensive, well-organised, detailed, technically correct, and pertinent strategies when compared to risk assessment generated by human experts. Comparatively, human responses were vague, broad, and followed a narrative style and needed more time to produce. The study suggests that GenAI's role in risk management is promising when complemented with human expertise and judgement using data-driven dashboards. These dashboards could enable real-time reporting and flag potential issues in building operations.

Several authors see opportunities in using GenAI and machine learning to enhance the efficacy of predictive building maintenance strategies [28,40,53]. They argue for leveraging the use of AI models to detect potential failures in building operations, such as lighting systems, thereby improving the user experience. Wahba et al. [44] pointed out the development of alternate models to improve thermal comfort prediction in the building refurbishment process.

In HVAC system management for building operations, the IoT enables mass data collection from smart devices of building users to enhance thermal comfort while reducing energy consumption. With the objective of balancing indoor thermal comfort, air quality, and energy consumption, the integration of older generations of AI tools in thermal comfort control systems has gained significant attention since the 1990s. Wahba et al. [44] investigated the use of innovative GenAI and LLM in HVAC's thermal control to strike an optimum balance. Their systematic literature review finds that AI tools assist in interpreting and tracking data collected from HVAC control systems. Many research results enabled a significant reduction in energy consumption while maintaining acceptable thermal comfort. Despite recent advancements in the computational power of AI tools, Wahba et al. [44] found that it is still limited in real-life applications due to a lack of understanding of the modelling logic that GenAI uses.

In heritage buildings management and preservation, Spennemann [54] acknowledged the values that five GenAI chatbots (namely ChatGPT 3.5, Bing Chat Balanced, Bing Chat Creative, DeepAI Genius, and Google Bard version 2023.07.13) provide in extracting and synthesising extant and large-text information to recognise patterns and connections in the design which could be ignored by human experts. Spennemann [42] finds that GenAI output may still require human judgement for confirmation because some of these chatbots rely on less credible open-source data, which may not be reflective of the actual project context, heritage values, and authenticity. These issues could be better served by training

GenAI models based on international heritage preservation guidelines and the historical context of the design.

### 3.7. Urban Governance

Figure 9 presents the urban governance thematic tree. In urban governance, Alahi et al. [21] linked smart home automation and smart cities and urban governance. They postulated that GenAI could collectively analyse the information harnessed from smart homes to help in smart city planning. Considering energy consumption as an example, peak operation hours favoured operation settings and endless opportunities to explore and improve the ways domestic environments function more accurately. Fan et al. [29] found that urban centres may optimise energy use and lower carbon emissions by combining AI algorithms with renewable energy sources like solar and wind power. This will ensure ecologically friendly urban centres and lower energy prices for businesses and inhabitants. Smart urban centres may become more productive, efficient, and environmentally sustainable by utilising these technologies, ultimately improving the living standard for residents.

GenAI has a wide range of possible uses in intelligent sensing and monitoring using data analytics dashboards. AI-powered monitoring systems can improve public safety, streamline traffic flow, and effectively control energy use in smart urban centres [4]. Mathararachchi et al. [32] presented an approach for optimising GenAI chatbots to analyse large amounts of information gathered from sensors in energy infrastructure (IoT) to assist in urban-scale decision-making. The strategy aims to reduce carbon emissions from energy infrastructure and was tested at the facilities of La Trobe University—a large, multi-campus tertiary education institution in Melbourne, Australia. The results highlight the effectiveness of the proposed method in optimising GenAI chatbots towards net-zero emissions energy IoT infrastructure.

Several authors postulated the integration of GenAI in the built environment to achieve SDGs [29,38,45]. For instance, Wang et al. [45] emphasised on SDG11—sustainable cities and communities; SDG9—industry, innovation and infrastructure; and SDG12: responsible consumption and production. LLM can facilitate the low-carbon energy transition in urban planning and green infrastructure. Wang et al. [45] concluded that GenAI has the potential to contribute to most of the UN's SDGs for a sustainable future. However, their research recommended that such contributions must abide by regulatory frameworks to ensure accountability, safety and ethical procedures that address privacy.

Reja et al. [39] presented the advantages of using LLMs to analyse data collected from DT of cities and infrastructure using real-time IoT systems. Their review determines that with the continuous evolution of GenAI's decision-making abilities, the process starting with data analytics up to decision-making in cities' infrastructure could be independently handled by GenAI. The extensive review by Cheng et al. [23] further breaks down the roles LLMs can play in a wide range of sustainable urban development applications. These roles are as a simulator, decision-maker, and expert advisor. The research finds that LLM has excellent potential to simulate low-carbon power scenarios, carbon market dynamics, climate risk assessments, and urban planning strategies. For example, in order to provide recommendations for sustainable urban development to planners, LLM agents can model the layouts, including parks, green spaces, and bike lanes, depending on environmental needs and urban development goals. LLM can also operate power systems, integrate renewable energy sources, predict demand patterns, and improve energy efficiency. Furthermore, LLM can provide expert advice in carbon accounting, satellite data interpretation, database management, and sustainable supply chain management.

Zhang et al. [55] identified computational capabilities in conversational GenAI to assist operations of energy infrastructure towards net-zero carbon targets. Wu et al. [56] found that GenAI creatively solve problems and optimises workflows in the urban planning proposals and the built environment industry. ChatGPT expedites writing, editing, and refining reports on the built environment, such as heritage and environmental impact assessments. De Silva et al. [25] investigated Scene Graph Generation (SGG)'s ability to interpret the volume of images of in-operation urban environments to enhance safety and efficiency for bicycle riders.

In smart city planning, Alahi et al. [21] examined the role of GenAI to analyse the vast amounts of data generated by IoT devices with accuracy and precision to aid decision-making. For example, public transportation, traffic lights, and citizens' daily activities generate enormous amounts of data (e.g., traffic flow, air quality, and generated waste), and AI can identify insights that can increase the efficiency and productivity of municipal government operations (e.g., infrastructure maintenance), enhance sustainability, reduce costs, and help reduce human errors. In smart city planning, algorithms like machine learning, deep learning, natural language processing, computer vision, reinforcement learning, and genetic algorithms can be used to analyse data, identify patterns, and produce projections based on trends that people can understand. Among other things, these algorithms can improve public safety, urban planning, and resource allocation. These algorithms are also capable of predicting crime hotspots, analysing patterns of energy consumption, and forecasting traffic flow.

On the applications of GenAI in urbanism, urban living, governance, and planning, Cugurullo et al. [24] expressed concerns on the increasing scale of AI dependency in cities to design, manage, and operate them instead of humans. For instance, the research perceives that a city run by AI, and not by humans, would challenge the autonomy of human stakeholders and struggle to be environmentally sustainable due to energy-intensive supply chains. In this case, it is essential that human stakeholders retain high levels of autonomy to act and make decisions in situations and contexts where the logic of urban AI deviates. Cugurullo et al. [24] were cynical about the social justice and equity of GenAI applications in urbanism, particularly in less democratic nations.

## 4. Conclusions and Limitations

GenAI is widely discussed in research related to the AECO. The literature holds an optimistic point of view of GenAI in AECO, which encourages development where needed. The examples in this review suggest that GenAI does not necessarily give better solutions in all instances. It would be worthwhile collecting information on the veracity of the "advice" from Gen AI, and it may be possible to highlight those areas of excellence and other areas that could be improved.

GenAI's applications in architectural design augment primary delivery outcomes, creativity dimension, and other quality measures (for example, aiming for higher levels of sustainability objectives). The full potential of the integration of BIM designs and GenAI has not taken place yet, but early data exchange tools between the two hold great promise, particularly when it comes to enabling the full live monitoring of project progress and enhancing formative project management. The role of GenAI in building operations is undoubtedly growing, with significant attention to enhancing sustainable outcomes such as reducing energy consumption and optimising maintenance decisions. In urban management, GenAI applications assist in guiding from higher-level decision-making down to controlling traffic flow. The two most noticeable advancements in the use of GenAI are the amount of discussion on its role in achieving sustainable goals and its increasing autonomy in the decision-making process. The coverage of the use of GenAI in construction and demolition holds the highest recognition, and accordingly, significant potential so far in the fields of construction site management, safety, training, contract administration, and waste management.

Nonetheless, this systematic literature review found three main gaps in the literature. Although articles reviewed in this study confirm that GenAI are actively being used in the AECO industry, most articles are literature reviews and prescriptive and opinion-based articles. Few empirical studies have been undertaken to assess the impacts of generative tools in the AECO industry. This indicates that the application of GenAI in AECO is limited. Most applications are still experimental and based on prospective benefits, which have not been validated in a large-scale industry application. The second gap is that most sectors covered in the analysed literature are construction and demolition, city and urban governance, and architectural design. The role of GenAI in the strategic definition and brief stage, in structural design, BIM, and in building operation is still understudied. This is evident by the lower sub-theme levels identified under these core themes. Other integral project stages and different project contexts have not been investigated and deserve attention, for example, different company and project sizes, contract types, cost planning and estimation, tender stages, project handover, geographical locations, and technology maturity levels. It is worth noting that there is still less dedication to researching novel domains in the AECO industries, reflecting the traditional culture of the construction industry. Leadership from influential stakeholders is needed to embrace the adoption of the latest technologies in the construction industry [57].

Lastly, no single author, publisher, or institute held a dominant position in the search on GenAI applications in the AECO industry in the literature. The contributions were widespread across various authors; outlined the diverse, explorative, and collaborative nature of existing efforts; and depicted a range of viewpoints and cumulative knowledge. While this may not be a gap, it indicates less dedication to researching this novel domain in the AECO industries, at least compared to the more established fields.

## 5. Future Research

This research shows that GenAI has brought transformative changes in AECO, but this horizontal systematic literature review finds that there are very few empirical investigations on the adoption of GenAI in the AECO industry. There is a pressing need to go beyond research reviews and examine views from the industry. Future research can collect and analyse primary information from the AECO industry and professional bodies to better understand the way(s) GenAI is affecting their line of work, and the main challenges of using it. First-hand information can also lead to comprehensively listing the common GenAI applications and programmes which are already in use in the AECO industries, and specifically at each of the project stages. Future works may prioritise professionals involved in understudied project stages (e.g., strategic definition and brief). Future research is expected to provide technical insights and cost–benefit analysis on the usefulness of the rapidly evolving field in AECO.

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