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AI applications for structural design automation

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ABSTRACT

In recent years, there has been an increase in artificial intelligence (AI) applications in the field of structural engineering. With the rapid development of AI, new opportunities have emerged to use this technology to generate and check the structural design. Over the last few years, there has been a sharp increase in the number of publications relating to AI applications in structural design. This paper presents a systematic review of previous studies on the applications of AI in structural design. A total of 134 papers were analyzed. The review shows that AI techniques have benefited engineers in generating optimized structural design solutions that meet the requirements of building codes and design standards. Additionally, challenges and future opportunities are presented and discussed. This review will contribute to the body of knowledge by summarizing the state-of-the-art of using AI technologies in structural design and exploring future research opportunities in this area.

1. Introduction

In recent years, the field of AI has witnessed significant advancements across various domains [1–3]. The driving forces behind these advancements are the core technologies of machine learning (ML), especially deep learning (DL) [4]. ML algorithms empower systems to learn from data, while DL, a subset of ML, has revolutionized fields such as computer vision and natural language processing (NLP). These developments, combined with the accessibility of AI tools and their integration with other technologies, offer potential for various industrial and societal progress. State-of-the-art tools like ChatGPT [5] have enhanced more natural human-machine interactions, while advancements in generative AI have expanded the horizons of human creativity and problem-solving capabilities.

ML has proven to be a valuable tool for a diverse range of applications in structural engineering [6–8]. In structural engineering, the integration of ML has started to change decision-making processes [1]. Leveraging its analytical capabilities, ML delves into data to generate alternatives aligned with project requirements. Its role also extends to predicting and ensuring structural integrity. Functioning as a knowledgeable collaborator, ML aids engineers to ensure precision in various aspects.

One important aspect of structural engineering is the design and optimization of structures [6]. In the intelligent structural design field, the data feature representation is crucial [9]. Data collection involves gathering essential information on structural performance requirements and results from structural analysis tools. Design generation and optimization of design solutions form the core components of structural design. Lastly, compliance checking is an essential step in ensuring structural safety and conformance to building code requirements. This whole process can be very complicated, especially for complex structures like high-rise buildings, which sometimes require extensive experience and numerous iterations. The number of iterations required generally depends on the experience and expertise of designers and of course the complexity of the structure.

Researchers have started to use ML to aid in this process. Through learning from previous designs, ML has the capacity to generate new designs by considering the experience embedded in those previous iterations. This is particularly evident in the design of reinforced concrete shear wall layouts, where ML has proven to be exceptionally useful [8]. Besides shear walls, researchers are also exploring the application of ML in other areas, such as determining member sizes [10] and arranging steel rebars in reinforced concrete [11], showing the versatility of ML in addressing various aspects of structural design.

Another important aspect of structural design is to ensure compliance with regulatory documents. Traditionally, this process has been labor-intensive, relying on manual efforts from experts to ensure designs align with established codes and standards [12]. However, the advent of automated compliance checking (ACC) methods using AI has changed how this process works. These methods have been applied in various fields, including construction safety requirements [13], fire safety [14], energy regulations [15] and building permit requirements [16].

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Researchers have explored the application of NLP and Building Information Modeling (BIM) [17–19] to interpret rules from regulatory documents, transforming them into computer-readable rules for ACC. DL, with its advanced techniques, has broadened the scope of ACC, considering the complicated structure in codes [20]. Within the checking phase, researchers have explored areas such as information extraction [21], transformation [22], compliance reasoning [23], deep learning-based methods [13,21,24–27], and BIM-based compliance checking [28–31].

Enabling a fully automated design process requires the integration of both design generation and compliance checking aspects, working collaboratively to ensure a smooth workflow. Recent research efforts highlight the advancements in generative AI design for building structures. Liao et al. [9] and Jang et al. [32] summarized the latest developments in generative AI building design, comparing different evaluation methods for the results generated by AI. This work contributes to understanding and assessing the effectiveness of AI-generated designs in the context of building structures. Additionally, Shamshiri et al. [33] focused on the analysis of text-based information extracted from regulatory documents, including building codes and design standards. Their approach involved leveraging text mining and NLP techniques to extract valuable insights from textual information. Their study underscores the importance of incorporating AI methods not only in the design phase but also in the analysis of textual data relevant to regulatory documents, ensuring a more comprehensive and automated approach throughout the entire design and construction process.

While earlier review papers separately summarized AI applications in design generation [9,32], design optimization [34] and compliance check [33], limited effort has been given to integrate these critical components in structural design. In practice, structural design is a complete process that involves both the creative development of design solutions and the verification of their compliance with regulatory standards. With the rapid advancement of AI techniques including the recent rise of large language models (LLMs) and the emergence of new research objectives, bridging design generation and compliance checking has become increasingly important. This review aims to address this gap by synthesizing recent developments that link these two domains. It offers a comprehensive overview of AI applications in structural design generation and compliance checking, highlighting the methods adopted and the specific challenges addressed in each study.

The remainder of this paper is framed as follows: Section 2 presents the approach to select literature for review and an analysis of publications. Section 3 concentrates on AI-assisted design generation. Section 4 describes recent studies on automated compliance checking. In Section 5, challenges are presented. Conclusion and future opportunities are discussed in Section 6.

2. Analysis of publications

This study is dedicated to exploring the integration of AI techniques into structural design. The focus is on obtaining information from refereed journal papers and ignoring conference articles and books. The Scopus database, recognized for its extensive repository, was the primary resource for paper selection [35]. This approach ensures a comprehensive and high-quality foundation for the insights and findings presented in this study.

The search process is shown in Fig. 1. The search strategy involves specific keywords grouped into two categories: design generation and compliance checking. Given the recent surge in AI development, the search covers the past ten years, aligning with the period of substantial computational advancements. To be more efficient, the search in this study utilized keywords. For the design generation area, the keywords used were: “Structural Design” AND ““Intelligent” OR “Automated” OR “Smart”” AND ““Networks” OR “Deep Learning” OR “Machine Learning” OR “Artificial intelligence””. Then the document type was set to Article, the year between 2015 and 2025, the language to English, and the

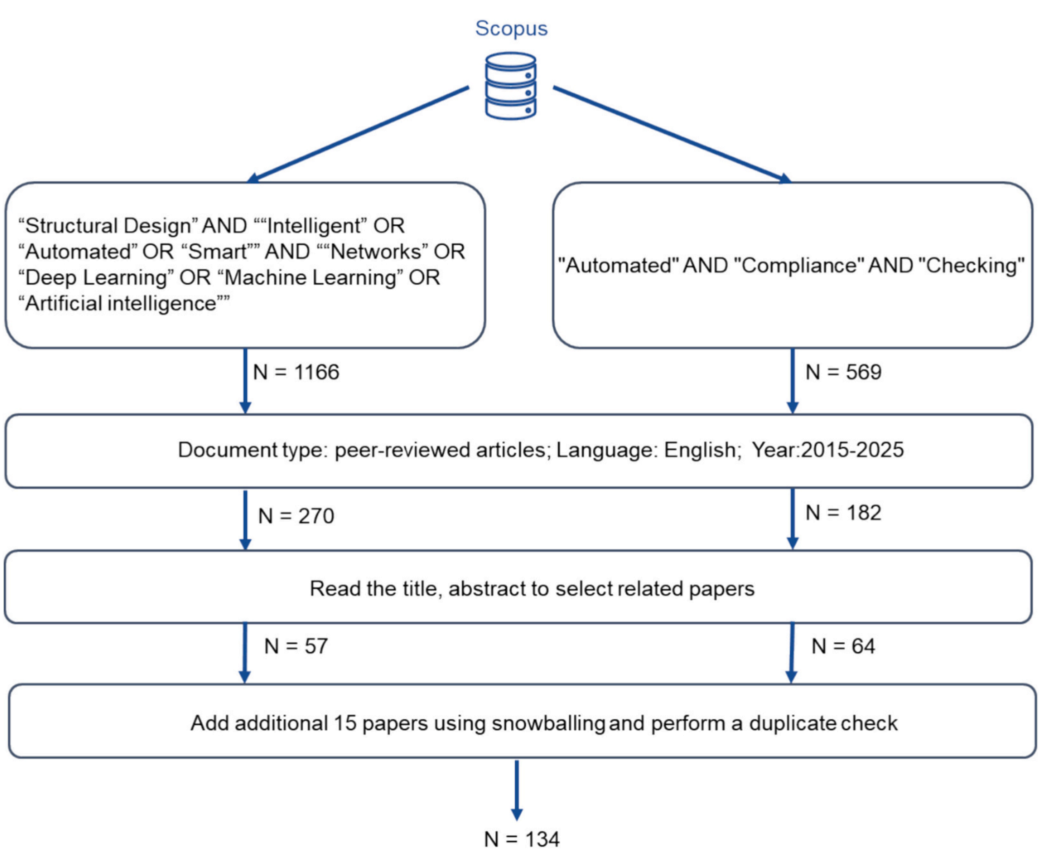


Fig. 1. Literature selection process.

subject area to Engineering. The initial search yielded 270 papers, and subsequent manual screening excluded the majority of the papers to keep those papers that focused primarily on design of structures. Specifically, papers related to property prediction, product design and manufacturing, and thermal analysis were excluded. Based on a review of the titles and abstracts of the 270 papers, 57 papers were eventually selected. Likewise, for selecting papers related to 'checking', the keywords used in the search were: "Automated" AND "Compliance" AND "Checking". Initial results yielded 182 documents, which were reduced to 64 after rigorous filtering by reading the titles and abstracts. Acknowledging the keyword limitations, the snowballing approach contributed 15 more papers, and deleted two identical papers in both parts, resulting in a total of 134 for structural design.

The annual publication data, as illustrated in Fig. 2, indicates a notable trend—a substantial surge in the number of relevant papers over the past four years. This pattern underscores the growing importance of AI applications in both design generation and compliance checking. In the field of design generation, 2021 marked a significant year, witnessing a notable surge in the number of published papers. In 2021, researchers [8,36,37] began to utilize deep learning models for structural design. It is noteworthy that the publication counts from 2021 to 2024 (assessed on July 14, 2025) are particularly high, indicating increased interest and robust research activity during this period. Looking ahead, it is anticipated that the publication counts for 2025 and beyond will continue this upward trend.

Regarding publication sources, as summarized in Fig. 3, *Automation in Construction* ranks first with 29 articles, accounting for 21.6 % of the total, followed by *Advanced Engineering Informatics* and the *Journal of Computing in Civil Engineering*.

Utilizing the VOSViewer tool, a co-occurrence keyword analysis generated insightful knowledge maps. Fig. 4 indicates crucial terms and connections from both research domains, highlighting central themes and key concepts. The co-occurrence analysis of keywords offers three insights:

(1) The green group focuses on structural design, with keywords such as deep learning, machine learning, shear walls, and optimization. These studies mainly apply AI to structure-related tasks.
(2) The red group is about automated compliance checking and natural language processing, with keywords such as building codes, semantics, and language models. This cluster connects AI, including using large language models, with checking if designs meet rules.

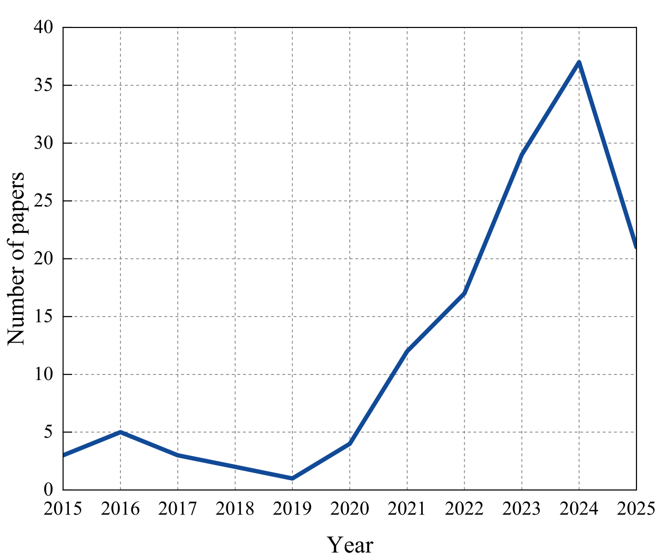


Fig. 2. Distribution of papers between year 2015 and 2025.

(3) The blue group centers on architectural design and BIM. It includes keywords like automation and code compliance, showing how AI is used in design and modeling tools.

This map shows that different areas of research are closely connected through AI methods, such as deep learning, natural language processing, and machine learning. It also highlights that AI is being used to support both the design and checking stages of the building process, from structural design to code compliance.

3. AI-assisted structural design generation

In structural engineering, design often involves the search for possible solutions. AI excels in generating designs with similarities to previous instances. For structural design, while codes provide guidance, certain aspects of the process rely on the substantial experience of the designer. AI proves advantageous in these domains as it can learn from prior experiences, such as analyzing previous structural drawings. Following the training phase, these models emulate engineering decision-making, effectively contributing to the design process. Typically, in the whole design procedure, the preliminary step involves determining the layout of the structural systems, followed by detailed component design. Therefore, this review section is divided into two parts: layout generation and component design and optimization.

The publications were categorized based on building material and the focus of AI applications. The distribution of studies by building material type is shown in Fig. 5(a), with more than 60 % focusing on reinforced concrete structures, followed by steel structures (27.7 %). Regarding AI applications, the main research focuses are structural element layout design and structural element dimension design, as illustrated in Fig. 5(b). As for structural element layout design (Fig. 5 (c)), half of the studies concentrate on the layout of shear walls. This can be attributed to the fact that in high-rise buildings, shear wall layout design is highly iterative and time-consuming, even for experienced structural engineers [8].

The donut chart (Fig. 6) illustrates the distribution of AI models used in the reviewed studies, with each segment's size representing its relative frequency. Here, classical ML refers specifically to traditional machine learning methods that do not involve neural networks. GAN occupies the largest portion (37.5 %), highlighting its widespread application. Graph Neural Network (GNN) (20.8 %) also shows strong presence, followed by Artificial Neural network (ANN) (16.7 %), classical ML and diffusion models. Although RL is not shown in the chart due to its nature as a learning paradigm rather than a specific model type, it is commonly used in several studies for solving optimization or search problems where finding the optimal design solution is the primary objective [37].

This distribution suggests a strong preference for generative models such as GAN in solving design problems. Graph-based models like GNNs also play a key role in capturing spatial and topological relationships inherent in structural and architectural layouts. Meanwhile, traditional regression-based models, often falling under classical ML and ANN categories, are commonly applied in predictive tasks such as capacity prediction [38].

Fig. 7 presents the proportions of reviewed papers that (a) use drawings as input and (b) learn from past designs. As shown in Fig. 7(a), 57.1 % of the papers utilize drawings as input data, indicating a majority of studies incorporate visual or graphical information in their methods. In Fig. 7(b), 64.3 % of the papers are found to leverage past design data in their approach, highlighting a significant trend of learning from historical examples. Among the papers that do not learn directly from past designs, many still employ AI techniques, such as RL to search for optimal solutions [37]. These findings highlight the increasing emphasis on data-driven approaches in structural design, whether through experiential knowledge or advanced AI-driven exploration.

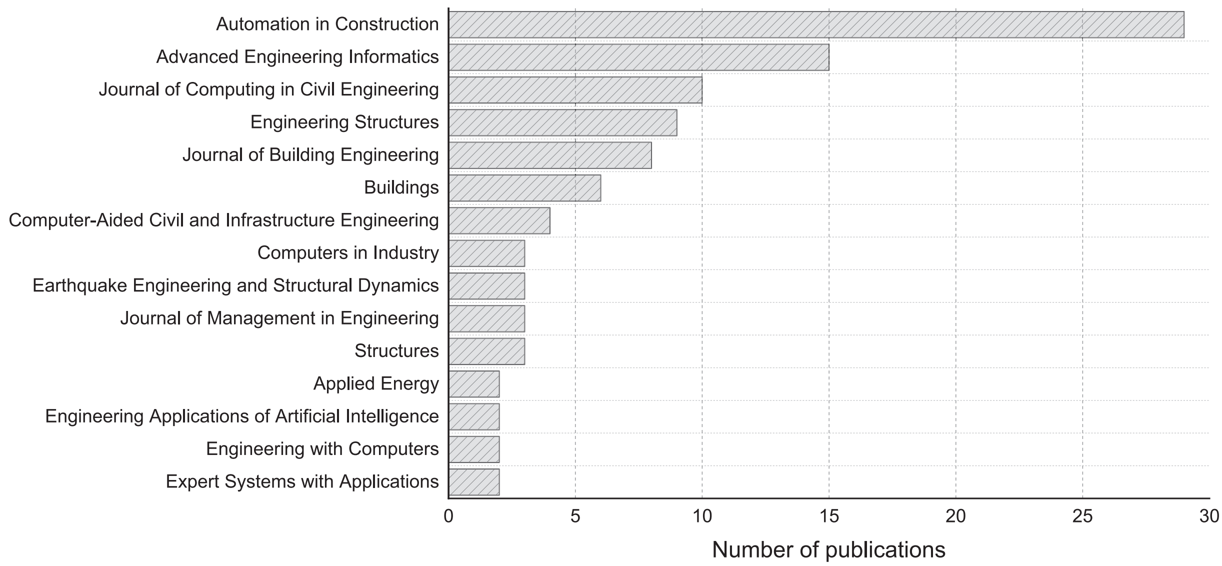


Fig. 3. Journals with more than one publication.

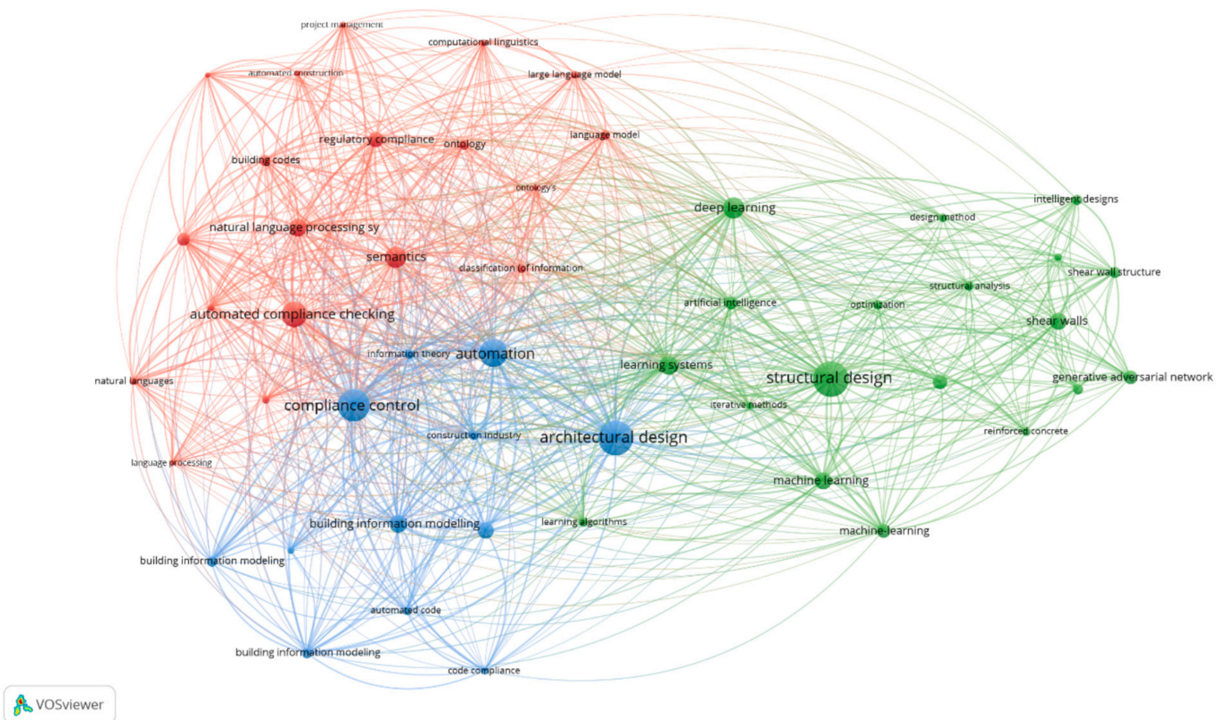


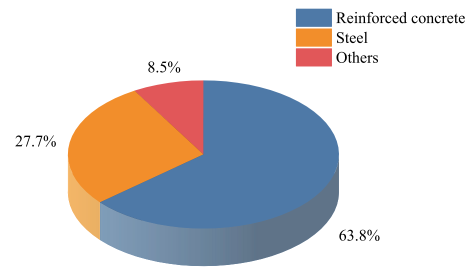
Fig. 4. Mapping of co-occurring keywords.

3.1. Layout generation

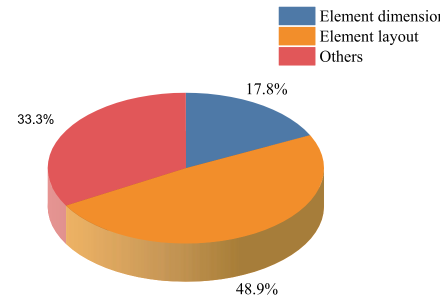
In the structural design process, especially for high-rise buildings, the initial stage revolves around designing component layouts. This process, while crucial for determining the arrangement of various structural elements, often requires iterative efforts and expertise [8]. To streamline this stage, ML can learn from past drawings created by experienced engineers. It can then generate design outcomes that closely resemble those of engineers. Various studies have been conducted on component layout design to enhance this aspect of the process.

Ampanavos et al. [39] introduced a system to predict the structural layouts from sketches and trained a Convolutional Neural Network (CNN) to perform this task. Their method focused on the column layout in single-floor plan using rigid metal frames. The whole process is iterative and, in each iteration, a local sub-problem is solved. Zhang et al. [40] presented an end-to-end method utilizing GNN to automatically generate structural topology for complex layouts. Zhang et al. [41] introduced a sketch-guided topology optimization approach based on the problem-independent machine learning (PIML) technique, focusing on enhancing the optimization process through the incorporation of sketch guidance.

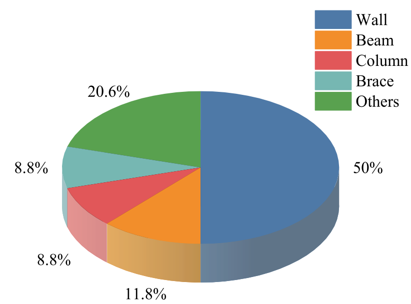
The design of RC shear walls is a widely discussed topic within the structural layout design, with various optimization approaches employed by researchers. Lou et al. [42] explored an extended Evolutionary Structural Optimization (ESO) method to perform the optimization of shear wall layout. Then in another study, Lou et al. [43]



(a) Percentage distribution of publications by building material type



(b) Percentage of AI applications in structural element design



(c) Percentage distribution of studies within element layout design

Fig. 5. Overview of categorized research focus.

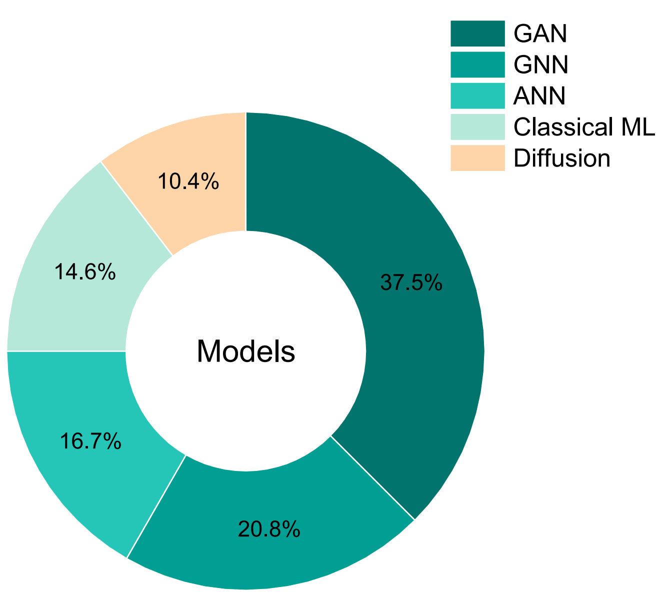


Fig. 6. Distribution of AI model families in the reviewed studies.

utilized the tabu search algorithm to optimize the shear wall layout. Additionally, Zhou et al. [44] applied a genetic algorithm with a greedy strategy, considering prior knowledge for shear wall layout design. While optimization algorithms play a crucial role, the expertise of human professionals is also invaluable.

To integrate human experience, Liao et al. [8] proposed a GAN-based method for the structural design of shear wall buildings. Fig. 8 provides an example of shear wall layout design. The proposed method (StructGAN) generates the layout of shear wall in the architecture drawings by learning from previous drawings by experienced engineers. The method was proven capable of generating shear wall layouts that are similar to those generated by experienced engineers. To better capture the correlations and distinctions between building components, Han et al. [45] proposed an optimized data representation and understanding method aimed at enhancing the accuracy and quality of structural design outcomes.

Furthermore, the properties of text can play a crucial role in shear wall layout design, providing valuable guidance. Liao et al. [46] introduced TxtImg2Img, a method that enhanced GAN-based approaches by integrating both drawing and text information. This innovative approach incorporated text (seismic design intensity and structural height) during training, resulting in a performance improvement of up to 21 %. To capture the correlation between key design features and the shear wall ratio, machine learning methods can be used to enhance prediction accuracy, and when combined with GAN-generated results, they further improve the performance of shear wall layout generation [47].

However, the design generated by the previous GAN method is not satisfactory in terms of the local details, particularly in the elevator shaft zone and the balcony zone. This is because the elevator shaft zone is the ideal location for shear walls, whereas in the balcony zone the shear walls are rarely needed. To tackle this issue, Zhao et al. [48] improved the local design of shear wall structures by artificially introducing a mask of critical zones in the preprocessing part of the method. This

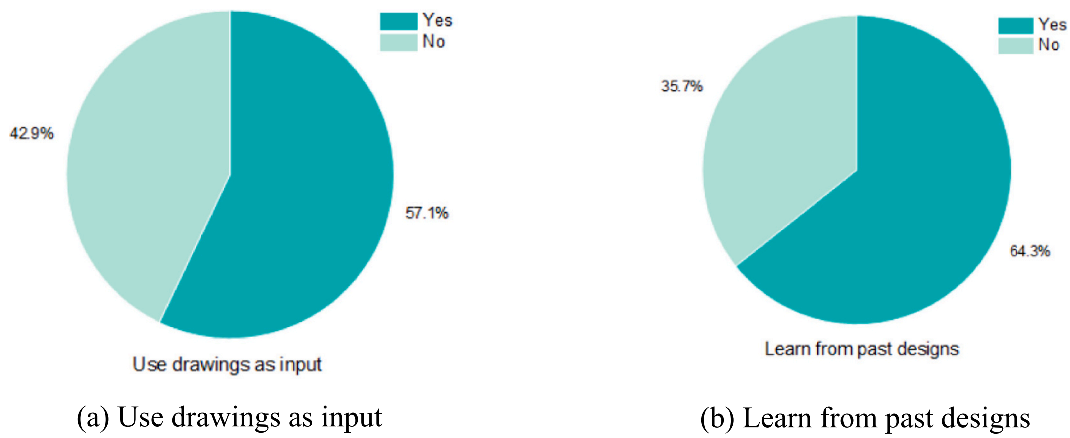


Fig. 7. Proportions of reviewed papers.

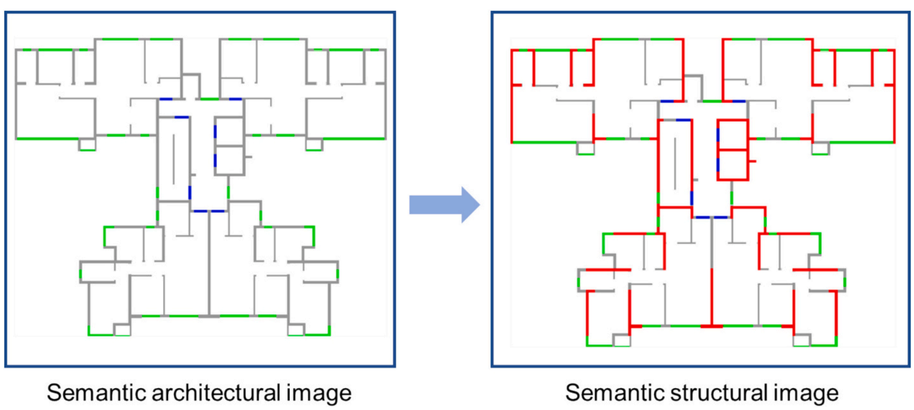


Fig. 8. Shear wall layout design example [8].

approach resulted in a more reasonable local layout of the shear walls in critical zones.

To facilitate the application of automated shear wall design, Fei et al. [49] proposed a practical application of GAN in the design of reinforced concrete shear walls. This application employed a cloud design platform to establish the environment, enabling the entire system to generate the complete schematic design phase for reinforced concrete shear wall structures. Pizarro et al. [50] proposed a streamlined model for shear wall buildings based on interconnected 3D beam-columns. This model enables a quick derivation of the fundamental period, base shear, and moment, offering flexibility to handle inputs from various sources like grid-based layouts or vectorized image floor plans.

The GAN require high-resolution pixel images, which may lead to huge computational workloads. Also, images cannot show the topological characteristics [51]. To address this limitation, graph representations have been introduced, as they can effectively capture and illustrate the relationships between nodes and edges [52]. For example, Zhao et al. [51] adopted GNN to design shear wall layouts. In their research, the building component was represented by graph nodes and edges, as illustrated in Fig. 9. Case studies demonstrated that the proposed model produced results that are similar to those of engineers, compared to the StructGAN method. More accurate shear wall layout design can be generated when seismic design factors [53] and expert experience [54] are incorporated. Additionally, diffusion models have begun to be used to generate shear wall layouts, demonstrating improved performance compared to GANs [55,56].

Besides the shear wall layout, DL models also provide layout design for other structural elements, like beams, columns, braces, bearings, etc.

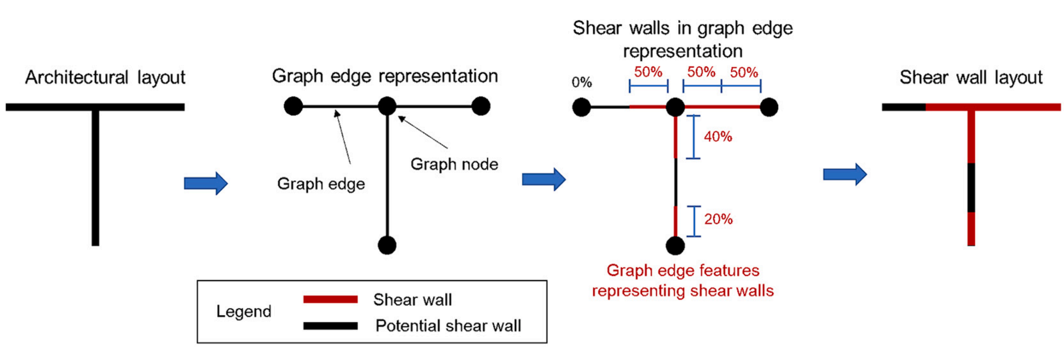


Fig. 9. Shear walls in the graph edge representation method (adapted from Zhao et al. [51]).

Zhao et al. [57] proposed an intelligent layout design method for beams of reinforced concrete shear wall structures. This method learned the existing designs and generated new layout schemes. A typical case study showed that the structural performance of the beam and slab designed by this method was comparable to that of competent engineers.

Also, GNN can work well in beam layout design. Zhao et al. [58] presented a method based on GNN to design the layout of beams in shear wall structures. Similarly, with the shear wall design by GNN, this method can achieve robust topological feature extraction capabilities. The result highly resembled those designed by engineers. Xia et al. [59] also proposed a co-design method using a GNN to simultaneously generate shear wall and beam layouts, aiming to achieve a higher Intersection over Union (IoU).

In frame structures, designing the layout of beams is also crucial. Zhao et al. [60] proposed an intelligent plan layout design method for frame beams based on GNN. Since the frame structure data was not sufficient, the authors presented a large-scale dataset generation method first on four common planar shapes of frame structures. The results showed that the GNN model can influence the performance of the beam layout design. Zhao et al. [61] introduced an automated method for plane trusses, incorporating user preferences to inform and generate the truss design. Shan et al. [62] introduced an integrated method for steel frame design utilizing a surrogate model. ML models can effectively reduce computational costs [62,63].

Regarding column and brace layout design, Fu et al. [64] proposed a GAN-based method (FrameGAN) to automate the layout design of steel frame-brace structures. The model can generate the layout of columns and braces. The authors utilized a dual GAN model to design the layout of columns and braces consequently. And better performance was achieved when additional design rules were integrated [65]. Additionally, a Graph Attention Network (GAT) was proposed for shell structure design, improving both design efficiency and performance [66]. Tan et al. [67] employed a diffusion model to pinpoint feasible positions for buckling-restrained braces, effectively reducing the search space for subsequent optimization.

In seismic design field, DL can also help seismic structural design. Lu et al. [68] developed a surrogate physics model to train GANs. The result showed that the proposed model produced design solutions in a shorter timeline than a competent designer. Liao et al. [69] proposed a GAN based method to generate the layout and parameters of seismic isolation bearings. In their study, the layout of seismic isolation bearings was generated by a GAN-based method. The pseudo-labels were used as the target data, indicating the location of seismic isolation bearing and shear wall component. After training, the method was able to design seismic force-resisting systems that incorporated seismic isolation bearings.

The design process can be further enriched by incorporating architectural floor plans, which play a crucial role in the early stages of building design. This includes the transformation of sketches [70], the generation of architectural layouts from them [71] and similar floor plan layout retrieval to facilitate draft design [72]. These approaches not only improve design efficiency but also enable designers to explore a wider range of layout alternatives with reduced manual effort.

Overall, it can be concluded that AI significantly supports the design of component layouts. The methods have the capability to learn from past designs, while simultaneously incorporating domain knowledge and rules to enhance accuracy and generate more sensible outcomes. Shear wall layout stands out as a popular application for AI-assisted design due to the complex non-structural (e.g. alignment with non-structural walls and elevator cores) and structural (e.g. reducing torsional effect due to eccentricity) requirements. Research for other structural elements follows, such as columns and braces [64]. It is also noted that most research studies so far have focused on concrete structures; similar studies on other materials such as steel [64,73] and wood [74] are limited. Another crucial observation is that the AI-generated layouts in the mentioned research often rely on learned experiences from the past.

It is acknowledged that past experiences may not always yield the most optimal solution. Therefore, more research focusing on utilizing AI for optimization is still needed, ensuring that the AI-generated layouts are not only learned from historical data but are also optimized for efficiency and effectiveness. This underscores the ongoing importance of advancing AI methodologies to further optimize and diversify the field of structural layout design.

3.2. Component design and optimization

Structural component design usually follows after the layout has been determined and the structural analysis has been done. Different components require different design methods. Although the design of a single component, like simply supported beams, can be simple and straightforward, the most optimal design can be challenging and time-consuming to obtain, especially if multiple design criteria are required to be met. Additionally, especially for high-rise buildings, single-member design cannot be conducted in isolation because the member design could have an impact on the design of other components, such as connections. Multiple iterations may be necessary to determine the most optimum design solutions for the complete system. Therefore, the use of AI models for structural component design may be an effective approach to generate optimum design solutions with reduced efforts, compared with the conventional method of trial-and-error.

Pizarro and Massone [36] utilized a regression model to predict the length and thickness of reinforced concrete building walls. A total of 30 features for each wall segment were calculated to describe each wall, and the deep neural network model (Fig. 10) can predict the thickness and length of the wall segments. The model has six fully connected hidden layers with 1024 neurons in each layer. In the other work conducted by Pizarro et al. [75], CNN models were proposed to generate the final engineering floor plan by combining two independent model predictions. Because in the engineering plans, engineers may add new structural elements for structural needs, compared with their previous study [36], this improved framework was able to generate new structural elements not present in the architecture drawing. Similarly, So et al. [76] employed an artificial neural network to efficiently predict beam cross-section designs.

Reinforcement learning is also a direction for component design. Jeong and Jo [37] used deep reinforcement learning (DRL) to design reinforced concrete beams. The agent observes the current state of the environment, selects an action, receives a reward, and the environment transitions to the next state, following a repeating cycle. The DRL agent was able to design the beam with the lowest cost while ensuring flexural moment and shear design requirements. In the training phase, there is no need to label the dataset; instead, it can train itself by exploring different design options and maximizing reward. When using this method, the reward function was considered a critical component for further use in structural design automation. Similarly, DRL was utilized in designing steel frame structures, achieving faster results than manual methods [73]. Lin et al. [77] applied DRL to the design of steel–concrete composite beams, demonstrating promising results with reduced time consumption.

In the domain of detailing rebar in reinforced concrete design, the prevention of clashes between rebars holds paramount importance. Conventionally, the layout of reinforcement bars heavily depends on the experiential knowledge of engineers, resulting in labor-intensive processes. To overcome this challenge, Liu et al. [78] proposed incorporating optimization algorithms to facilitate the automatic generation of rebar layouts. This innovative approach aimed to streamline the reinforced concrete design process, reducing manual effort and potential clashes between rebars.

Another research presented by Liu et al. [79] used a BIM-based framework that integrated GAN and DRL to automatically generate clash-free rebar designs in prefabricated concrete wall panels (PCWPs). They first used GAN to generate rebar designs, and then in the DRL

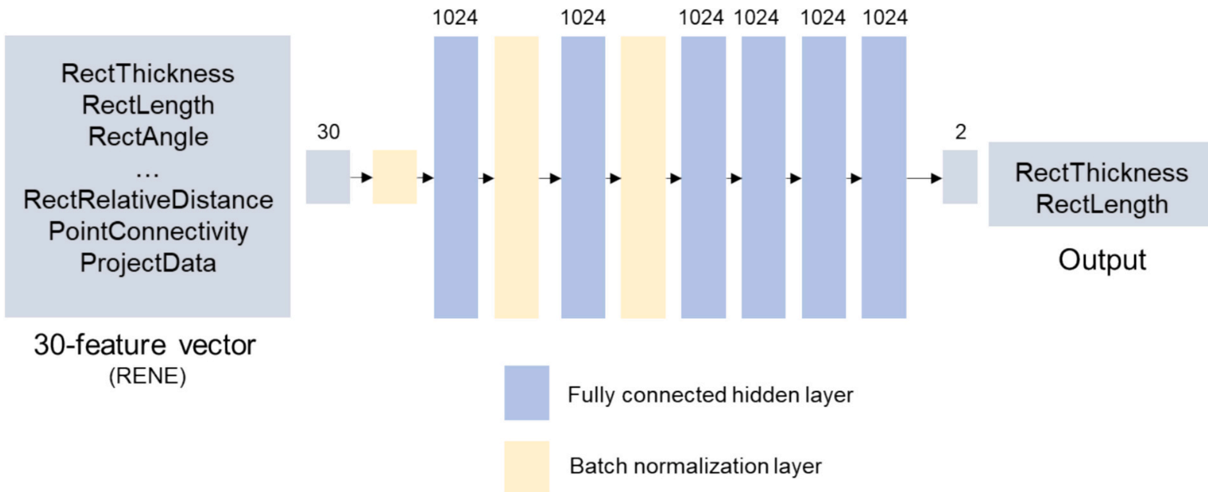


Fig. 10. Model architecture for predicting the wall thickness and length (adapted from Pizarro and Massone [36]).

process, the agent selected the suitable actions and converged to the optimum through practical training. In the last step, the 3D rebar models were generated in BIM. To achieve design optimization for the rebar layout in a reinforced concrete beam, Li et al. [11] proposed a framework for rebar design optimization in reinforced concrete structures. GNN was utilized to represent the relationship between different rebar groups in the components. The study involved two GNNs, one for rebar layout proposal in reinforced concrete and the other for clash diagnosis. The example showed that the proposed approach can generate practical rebar layouts without clash.

For high-rise buildings, the design involves several steps. The schematic design, as the initial phase of the design process, exerts the most significant influence on the entire design process. Chang and Cheng [80] proposed a method to reduce the iterative industrial structural design workflow by training a structural simulator. Fei et al. [10] proposed a novel method that considers domain knowledge in the GAN method when choosing the component size in framed tube structures. Considering the design conditions and the structural layout drawing, the model can offer appropriate sizes for each component with expert experience and domain knowledge. The main contribution of the paper was that it was able to accumulate expert experience and master domain knowledge.

Similarly, in the schematic design stage, Feng et al. [81] adopted a GAN-based method in the intelligent cross-sectional design method of shear wall components. The authors embedded rules in the GAN to achieve a rapid and accurate cross-sectional design of shear wall components. Qin et al. [82] introduced heterogeneous graph neural networks (HetGNNs) for component size design in RC frame structures, enabling rapid sizing completed in under one second. Hayashi and Ohsaki [83,84] employed graph embedding (GE) and Reinforcement Learning (RL) for discrete cross-section optimization in planar steel frames. Here, the RL agent strategically minimized the total structural material volume while adhering to practical constraints. Improved GE formulations empowered the agent to comprehend the structural attributes of columns and beams. Hoseini et al. [85] optimized brace cross-section areas using AI algorithms, demonstrating lighter design solutions compared to conventional design examples.

AI-based structural design methods have demonstrated potential to enhance the overall efficiency and consistency of the design process. In recent studies, researchers have compared AI-generated designs with those produced by engineers, using a variety of evaluation metrics. These comparisons, summarized in Table 1, indicate that AI-based methods can achieve performance levels comparable to manual design. The degree of similarity, however, varies depending on the complexity and specificity of the design task.

Table 1
Summary of recent studies comparing AI-based and manual structural design.

References	Structural design object	Evaluation metrics	Results
[65]	Column and brace layout	Story drift ratios	Slightly higher than engineering results; 18.7 % difference
[73]	Column and beam section	Material cost	8.3 % higher material cost than engineer's design
[51,56]	Shear wall layout	IoU	>0.5
[55]	Shear wall layout	Material consumption and max drift ratio	Material consumption slightly higher than engineer's design (average 4.8 %); differences in max drift ratio in x and y are 2.04 % and 3.52 %
[10]	Component size design	Material consumption and score	AI achieves 2.06 % lower concrete consumption. 3.48 rationality quantification, very close to engineer's design (3.49) in rationality quantification
[75]	Engineering floor plan	IoU	0.627 ± 0.174
[36]	Wall thickness and length	R^2	0.995
[58]	Beam layout	IoU	0.7864

IoU: Intersection over Union between AI design and engineer's design.

In addition to the two categories layout generation and component design, other types of design are also using AI for the structural design, such as intelligently partition grids to generating coherent and well-defined free-form grid structures [86], constructability of rebar cages [87], design of wind turbine tower [88]. LLMs have recently started to gain attention in design-related tasks. Their ability to understand and generate structured content makes them promising tools for supporting design processes [89–91].

To conclude, the primary focus of structural design revolves around the design of essential elements such as beams, columns, lateral load-resisting systems and their connections. While relevant research has been conducted on beams, columns and shear walls, there have been fewer reported studies on the use of AI technologies in connection designs [38]. For both timber and steel structures, the design of connections can be very challenging, due to the need to consider a wide variety of structural and non-structural requirements, which include fire protection, fabrication procedures, esthetics, etc. The determination of member and connection sizes is the core of the structural design process, and AI emerges as a valuable tool for optimizing this task, potentially reducing the time spent on the process compared with the traditional iterative procedures. It is also noted that, since AI model performance heavily depends on the training dataset, data enhancement is essential for increasing data diversity and improving training robustness [92].

4. Automated compliance checking

In the realm of structural design, ensuring compliance with standards and codes is also critical. In practice, when the design of a structure is completed by a qualified structural engineer, the design will be evaluated to ensure that the design meets the requirements of relevant building codes and design standards. This process is referred to as compliance checking in this paper. Traditionally, this has relied on manual processes that are prone to errors and time-consuming. Recognizing this, a surge of research has emerged in recent years, delving into ACC to enhance the accuracy and efficiency of this crucial procedure.

The keyword relationships specific to ACC are summarized in Fig. 11. This keyword co-occurrence map highlights the main research themes in automated compliance checking. Closely connected keywords reveal strong links between BIM, natural language processing, AI techniques, and rule-based checking. The network suggests an interdisciplinary approach across design, modeling, and compliance tasks.

ACC aims to automate the evaluation process, replacing the manual assessments with more reliable automated procedures [93]. This exploration of ACC unfolds in three key dimensions: rule-based ACC, which centers on text information extraction [94,95], rule representation [96] and reasoning [23]; DL-based ACC, which harnesses DL methods [20,21,24,25,27,28,97,98]; and strategies to enhance interpretability, which addresse challenges in ACC processes [99–106]. LLMs are also a new and growing method used for ACC [107–110]. This section presents a comprehensive overview of the advancements in ACC, emphasizing the integration of rule-based, DL-based, and LLM-based approaches. The applications of ACC usually lie in text-related clauses. These clauses form the basis for compliance checking, ensuring that designs adhere to established standards and regulations.

4.1. Rule-based automated compliance checking

In ACC, rule interpretation plays a crucial role, involving the translation of rules from text into a machine-understandable format. Zhang and El-Gohary [22] proposed an approach for automated rule extraction comprising five steps. The first step involves text classification to recognize relevant sentences in the documents. Subsequently, the information extraction step identifies words and phrases in these sentences. Following this, the extracted information was transformed into logic clauses for implementation and evaluation.

Before extracting rules, the text undergoes classification into predefined categories to selectively retrieve pertinent clauses and filter out irrelevant ones, thereby enhancing the efficiency and accuracy of rule extraction. Salama and El-Gohary [111] introduced a semantic, machine learning-based text classification algorithm designed to classify clauses and sub-clauses within general conditions, thereby supporting ACC. In the extraction stage, Zhang and El-Gohary [94] proposed a semantic NLP approach for automatically extracting information from textual documents related to construction regulations. Their study incorporated pattern-matching rules and conflict resolution rules, utilizing NLP techniques to capture the syntactic features of the text. Beach et al. [112] utilized the Requirement, Application, Selection, and Exception (RASE) method as the rule representation approach. They further employed a set of formulas to determine and articulate the rules within their study.

Challenges arising from text complexities, including hierarchically structured text, can pose difficulties. To overcome these challenges,

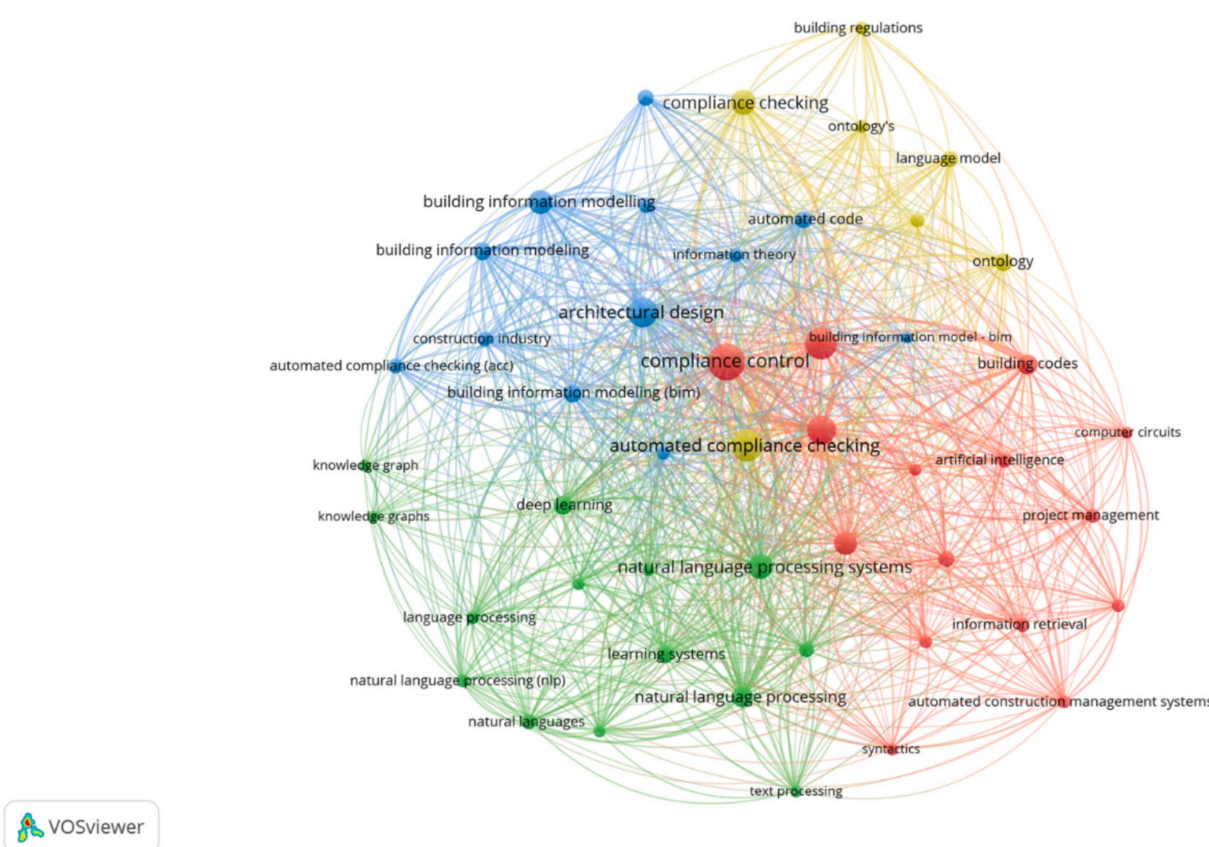


Fig. 11. Co-occurrence map of ACC studies.

Zhou and El-Gohary [95] introduced a semantic information extraction method. This method was designed to automatically extract building energy requirements from specifications, offering a solution to navigate and extract relevant information from complex text structures. Following information extraction, there is a crucial transformation phase. Zhang and El-Gohary [22] expanded on this by considering both syntactic and semantic text features simultaneously, integrating domain ontology to prevent ambiguous term interpretation. Subsequently, Zhang and El-Gohary [23] proposed a novel first-order logic-based representation for compliance reasoning in building designs, enhancing regulatory compliance checks.

Ontology-based methods play a crucial role in capturing the semantics of textual information, and several papers have explored this approach. Zhou and El-Gohary [113] introduced an ontology-based text classification algorithm to refine the classification process. The proposed approach has the potential to be applied to other domains with varying ontologies. However, its performance is contingent upon the quality of the ontology utilized. Later, Zhou and El-Gohary [114] presented a domain-specific text classification algorithm aimed at enhancing classification processes. In a related field, Zhong et al. [115] developed four specific ontologies to represent knowledge.

Additionally, Jiang et al. [116] introduced a multi-ontology method to facilitate ACC, employing rule-based reasoning to generate comprehensive checking reports. Ontology mapping offers a feasible approach to enriching design information semantically. Li et al. [117] introduced a method for representing building codes, breaking down building code information into five distinct parts. They established a mapping between concepts in building information ontology and code knowledge concepts, facilitating the automatic generation of reasoning rules.

Towards achieving full automation, Zhang and El-Gohary [118] introduced a unified system integrating NLP-related techniques. This comprehensive system comprises modules for information extraction and transformation from building codes, design information extraction from BIMs, and compliance reasoning. Addressing practicality, Xue and Zhang [119] expanded the rule set iteratively, balancing rule validity, generality, and compatibility with existing rules. This iterative expansion method effectively broadened the scope of checkable code requirements in ACC systems. Moreover, Zhang et al. [120] identified essential capabilities for rule representation in health care design regulations, providing criteria to enhance automated code compliance for the built environment. This research provided valuable insights by offering a checklist for future representation development and establishing criteria for evaluating rule representation methods.

It is common that non-textual information in the building code and design standards contain essential information for design [121]. Previous research mainly focuses on text and other types of information still remain to be processed. To solve this, Xue et al. [121] proposed a method to extract tabulated information in the building codes to assist ACC systems and generate rules. The authors estimated that a substantial number of logic rules, exceeding 1500, could be derived from tables found in both the training and test datasets, originating from a collective pool of 17 tables. Recent advancements have furthered the ACC field. Zheng et al. [122] introduced a knowledge-informed framework leveraging NLP techniques. Their approach involved establishing an ontology to systematically represent domain knowledge, incorporating semantic alignment and conflict resolution mechanisms. Additionally, an algorithm was devised to determine appropriate SPARQL functions, facilitating complex rule interpretation by generating SPARQL-based queries tailored for model checking purposes.

In summary, the reviewed studies collectively emphasize the pivotal role of ACC in structural design. The journey from rule interpretation to compliance reasoning involves sophisticated techniques, including ML, NLP, ontology-based methods, and advanced reasoning models. Researchers have strived to bridge the gap between textual information in regulatory documents and machine-understandable representations, allowing for efficient rule extraction and interpretation. Ontology-based approaches have been instrumental in capturing semantic relationships and enhancing rule representation. Furthermore, recent developments, such as iterative rule set expansion and the incorporation of tabulated information, showcase the field's evolution to address complex challenges. As ACC advances towards full automation, the integration of diverse techniques and frameworks, informed by domain knowledge and practical considerations, remains essential for shaping the future of intelligent and comprehensive compliance checking in the built environment.

4.2. DL-based compliance checking

Rule-based methods are adept at converting information into computer-readable formats, but they often lack adaptability and scalability, especially when dealing with diverse documents or undergoing major updates. In such scenarios, DL-based methods offer a solution by automatically transforming code sentences into formats that computers can process. Table 2 summarizes the main DL-based compliance checking models and their targeted problems.

Usually, the characteristics of different types of regulatory documents are not always the same. To solve this issue, Zhang and El-Gohary [21] employed bi-directional LSTM and CRF models with transfer learning strategies for extracting semantic and syntactic information elements from building code sentences, as illustrated in Fig. 12. The model was trained using different building code sentences and general English sentences. The trained model performed consistently in different types of regulatory documents. Subsequently, Zhang and El-Gohary [24] further suggested a hierarchical approach to decompose sentences into units. A DL-based method was proposed to automatically extract semantic relations and transform building-code sentences into hierarchies using these relations. The trained model achieved 94 % accuracy, showing the model's strong capability in semantic relation extraction and requirement hierarchy comprehension.

Later, Wang and El-Gohary [25] employed DL techniques to identify entities within regulations and address referential ambiguities present in the extracted entities. Bloch et al. [97] employed GNN to assess code compliance for single-family houses. They found that GNN can be a valid direction for future research. GNNs enhance traditional ML by extending its capabilities to regulations governing the relational aspects between building elements.

Another challenge faced by numerous ACC systems is that they mainly focus on simple sentences. Regulatory documents typically

Table 2
Summary of DL-based compliance checking.

Research	Models	Targeted Problems
Zhang and El-Gohary [21]	Bidirectional long short term memory networks (LSTM) and conditional random fields (CRF) models with transfer learning	Extract semantic and syntactic information elements
Zhang and El-Gohary [24]	Bidirectional LSTM and multilayer perceptron (MLP)	Extract semantics relations between words
Wang and El-Gohary [25]	LSTM and CNN-based model with pre-trained embeddings	Identify entities within regulations and address referential ambiguities present in the extracted entities
Bloch et al. [97]	GNN	Assess code compliance for single-family houses against specified requirements.
Zhou et al. [20]	Transfer learning	Label the semantic elements
Zheng et al. [98]	Pre-trained domain-specific language models and transfer learning	Assess the performance of different DL models
Zhang and El-Gohary [28]	Transformer-based method	Align the Industry Foundation Classes (IFC) and regulatory concepts

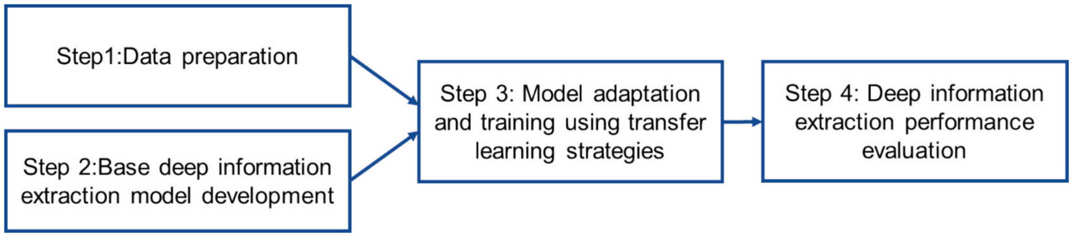


Fig. 12. Deep neural network-based method for deep information extraction (adapted from Zhang and El-Gohary [21]).

feature lengthy and intricate sentences, rather than being composed of single, straightforward requirements. To tackle this limitation, researchers have concentrated on expanding the scope of ACC to interpret a more diverse set of sentences. Zhou et al. [20] introduced an innovative framework for rule interpretation. In this framework, transfer learning was utilized for labelling the semantic elements. This framework was designed to analyze regulatory text in a manner similar to a domain-specific language. In comparison to prior methods, this new framework demonstrated an enhanced ability to interpret more intricate sentences, signaling a broader range of potential applications.

Recognizing that hidden knowledge plays a critical role in understanding relationships and obtaining properties, the incorporation of domain knowledge proves beneficial in the rule interpretation process. Zheng et al. [98] developed large-scale domain corpora and pre-trained domain-specific language models for the Architecture, Engineering, and Construction (AEC) domain. They systematically explored various transfer learning and fine-tuning techniques to assess the performance of pre-trained DL models across various NLP tasks. Results emphasized the better performance in NLP tasks with higher F1 score.

BIM is an important tool for ACC. Manual efforts are often needed when aligning the semantic regulations with BIM. To address this, Zhang and El-Gohary [28] proposed a transformer-based method to automate this process. The proposed method used a relation classification model to relate and align the IFC and regulatory concepts. The method used a transformer-based model and leveraged the definitions of the concepts and an IFC knowledge graph to provide additional contextual information and knowledge for improved classification and alignment. The results showed the importance of adjusting existing models with specific data in one domain or task.

In summary, the incorporation of DL-based methodologies into ACC systems marks a transformative advancement in the field. These approaches, encompassing diverse models and techniques, showcase considerable strides in addressing the inherent challenges of sentence diversity and automating the extraction of semantic information from building-code sentences. The integration of domain-specific knowledge with state-of-the-art DL methods holds the promise of enhancing the adaptability and scalability of ACC systems, thereby ensuring more effective compliance checking within complex regulatory environments.

It is crucial to acknowledge the dynamic landscape of DL models, characterized by rapid development and the emergence of novel techniques such as the LLMs [89]. While these advancements present exciting opportunities, their applications within ACC remain relatively limited at present. The integration of these cutting-edge methods into ACC frameworks holds the potential to unlock new dimensions of efficiency and accuracy, paving the way for enhanced automation and intelligence in compliance checking processes. As the field continues to evolve, there is a need for further exploration and experimentation with these innovative techniques to fully harness their capabilities and contribute to the ongoing refinement of ACC systems.

4.3. Enhancing interpretability

The effectiveness of ACC systems is intrinsically tied to the scope of checkable code requirements. Uhm et al. [99] discovered that less than 20 % of the gathered sentences could be translated to design rules. In a related study by Zhang et al. [100], the focus shifted towards addressing ambiguity in building requirements. They established a comprehensive taxonomy of ambiguity, marking the first systematic exploration and classification of ambiguous elements in building requirements. This work provided crucial insights into refining ACC systems by better understanding ambiguous elements within building requirements. Zheng et al. [101] employed an efficient text classification model based on a pre-trained domain-specific language model and transfer learning techniques to enhance interpretability. They evaluated more than 150 building codes in China and results showed that only 34.4 % can be interpreted. It is still difficult to transform the entire regulatory document into computer-processable information.

Knowledge Graph serves as a powerful tool for representing interconnected relationships [123]. In the context of design codes and rules processing, they have been applied to improve code representation by establishing semantic links between clauses [102], structuring rule information [103], identify non-compliant components [124] and support automated checks of BIM models [125]. These applications help bridge the gap between textual regulations and machine-readable formats, enabling more intelligent design assistance.

Another notable consideration in the realm of research is the generalization of proposed methods. Zhang and El-Gohary [104] addressed this concern by conducting a computability analysis through a clustering-based approach. They introduced a new set of syntactic and semantic features and complexity and computability metrics for computability analysis. Then sentence types were identified by the proposed features and metrics.

In the broader context of interpreting code requirements, researchers have tried generating intelligent code. Zhang and El-Gohary [105] introduced the concept of an intelligent building code. This concept served as a strategic response to potential errors in information extraction and transformation processes. By bridging natural-language requirements in the code with structured, computer-understandable semantic information (represented as semantic requirement hierarchies), these advancements contributed significantly to refining ACC systems. Intelligent coding not only aids in reducing errors but also aligns with the trend of improving the interpretability and reliability of rule-based systems within the domain of building code requirements. Lee et al. [106] introduced an approach to defining high-level implementable methods for improving low-level rule-checking procedures. Verb phrases were translated to code functions which can return real numbers or true/false value. This translation aims to reduce ambiguity while simultaneously representing the properties of objects in BIM applications.

4.4. Large language models

Recent advances in LLMs have opened new possibilities for ACC, a task that is fundamentally language-driven [126]. For example, LLMs can convert raw code clauses into executable queries through prompt engineering, eliminating much of the manual intermediate modeling that previously slowed ACC workflows [110]. Joffe et al. [107] created an open-source, retrieval-augmented LLM chatbot that answers questions about building codes and standards with source-grounded responses and interactive follow-up, demonstrating the scalability of LLM-based compliance assistance.

Madireddy et al. [108] embedded leading LLMs within Revit to parse building codes, autogenerate Python scripts, and flag non-compliant elements in real projects, greatly reducing review time while maintaining accuracy. He et al. [109] advanced this idea by combining retrieval-augmented generation with keyword search, enabling LLM to answer regulation queries. LLMs can also be combined with deep learning techniques to enhance their capabilities [127]. Collectively, these studies indicate that coupling LLMs with structured retrieval, domain-specific toolchains, and explicit script generation is emerging as a robust, scalable, and transparent paradigm for ACC.

In conclusion, the efforts to enhance interpretability within ACC systems have yielded notable progress, with several promising approaches contributing to a more nuanced understanding of complex regulatory requirements. One significant approach of improvement involves addressing ambiguity in building requirements, a critical aspect of ensuring accurate rule interpretation. The introduction of intelligent coding concepts, exemplified by the concept of intelligent building code, represents another noteworthy stride, creating a bridge between natural language requirements and highly structured, computer-understandable semantic information. Also, challenges exist in fully understanding and integrating information. This is the driving force behind ongoing efforts by researchers to enhance the interpretability of regulatory documents for building designs.

5. Challenges

Transitioning to automated structural design offers significant improvements in efficiency and accuracy, yet it also introduces substantial challenges. This shift from traditional manual methods to automated processes involves overcoming complex obstacles that highlight the intricacies of this transformation. To fully leverage AI's capabilities in structural design, it is essential to confront these challenges with comprehensive solutions. Based on analysis, key challenges are summarized as follows.

5.1. Data challenge

Data is fundamental to the effectiveness of AI in structural design. The quantity and quality of the data influence the performance of ML/DL models. However, the structural design field often suffers from a scarcity of datasets, primarily due to limited availability of public data sources [9]. Structural companies may be reluctant to share their data publicly. The size of the data still impacts the performance of the models [56]. Besides, datasets may lack even distribution across different ranges [128] and fail to capture complex structures [129], posing challenges for model training and generalization.

Additionally, structural drawings require pre-processing to extract usable information, but this extraction is not an easy task considering the complexity of structural drawings. The transition from traditional paper-based drawings to digital formats demands sophisticated scanning and digitization methods to guarantee precision and maintain data integrity throughout the process. Researchers usually use specific steps to processing their dataset, which is hard to be generalized [130].

In compliance checking, non-textual information in the regulatory documents is also crucial [121]. Exacting that information can be harder than text information. Moreover, the consolidation of diverse regulatory documents into a cohesive and accessible database can be an obstacle, as these documents often vary in format, structure, and content.

5.2. Design challenge

Capturing the intricate expertise and implicit knowledge of structural engineers is not an easy task. This knowledge, accumulated through extensive experience, is often tacit and not easily expressed, complicating its translation into algorithmic form. AI systems tasked with replicating such decision-making need to develop a sophisticated understanding of both the explicit rules and the subtle judgments that engineers make. While generative design algorithms can directly produce designs from end to end, their performance can be inconsistent, influenced by the limitations in capturing this deep expertise [48].

The curse of dimensionality significantly impedes structural design automation. Research typically focuses on isolated aspects of structural design, training models on specific variables [10,58]. However, comprehensive design automation requires integrating numerous components, necessitating multiple models that must function cohesively. This field involves managing thousands of variables—from material properties and geometric configurations to regulatory compliance. As the number of variables increases, the computational load may grow exponentially, thereby escalating the resources needed for generating or optimizing designs. Efficiently navigating this vast dimensional space demands not only robust computational power but also advanced algorithms designed to handle such complexity without compromising performance.

5.3. Integration challenge

Integrating AI tools into existing engineering workflows and systems presents a complex challenge. The integration process must ensure that AI outputs effectively align with the diverse requirements and practices of all participants involved in the design process. Additionally, achieving design automation requires various AI models to work together. However, coordinating these models to collaborate effectively poses its own set of challenges, complicating the overall integration effort. Moreover, structural design software and hardware are not readily compatible with newer AI technologies, necessitating significant modifications or comprehensive upgrades. Deploying DL models in structural design typically demands high computational power [49]. The financial burden includes not only the initial cost of developing and training AI models but also the ongoing expenses related to deploying and maintaining these solutions. Such costs can be high, potentially limiting access to AI technologies.

5.4. Performance challenge

AI in structural design is transformative, leveraging existing designs to enhance and streamline engineering solutions [8,10,58]. However, this approach often results in AI-generated designs that, while efficient, do not significantly surpass the capabilities of traditional engineering solutions. This limitation stems in part from AI's dependency on pre-existing design data, which inherently restricts its ability to propose novel engineering concepts that deviate from historical trends.

Furthermore, the crucial importance of structural integrity and safety in construction necessitates rigorous validation of AI-generated designs. Human engineers must verify these outputs to ensure they comply with stringent safety requirements. While ACC can assist this verification, this process is hindered by the shortage of professionals who possess a deep understanding of both structural engineering principles and advanced computer science techniques. The combination of these disciplines is vital not only for evaluating the reliability and safety of AI solutions but also for driving innovation within the field.

Additionally, as AI increasingly assumes decision-making roles in structural design, ethical and liability issues become more prominent [131]. One of the emerging challenges is determining responsibility for structural outcomes when AI-assisted designs are implemented. This issue highlights the need for clear guidelines and standards that define accountability in the use of AI in structural engineering, ensuring that safety and professional ethics are maintained in the face of rapidly advancing technology.

5.5. Assessment and supervision challenge

AI-generated structural design results may contain errors that pose serious safety risks if left undetected. Monitoring and early warning systems play a critical role in identifying such issues [132]. However, how to effectively monitor, prevent, and correct these errors during the design stage remains a challenge. Current AI systems in structural design rely heavily on human oversight, as there is no fully reliable mechanism to ensure the correctness of AI outputs autonomously. Unlike human designers, AI systems cannot be held accountable for mistakes, further emphasizing the importance of validation process. Furthermore, the absence of standard procedures for validating and correcting AI-generated design outcomes presents an additional barrier to practical adoption. Advancing efforts in this area is essential for the safe and trustworthy integration of AI into structural engineering practice.

6. Conclusions and future opportunities

The increasing number of publications on AI applications in structural design each year highlights AI's growing influence in this field. AI has proven invaluable in generating human-like designs inspired by historical engineering projects, effectively addressing complexities that typically demand expert knowledge. By utilizing past designs and integrating domain knowledge, AI enhances efficiency and practicality in design generation tasks. Furthermore, AI improves compliance checking processes by increasing both accuracy and efficiency. Advances in ACC have been driven by the uses of machine learning, natural language processing, and ontology-based techniques, which translate complex regulatory texts into machine-understandable formats, facilitating rule extraction and interpretation. LLMs are emerging as powerful tools to support the whole structural design process. Researchers are leveraging various neural network architectures tailored to specific structural design tasks, demonstrating AI's ability to complement human expertise.

This study underscores the inherent potential of AI-driven design generation and ACC in structural design. These pivotal advancements open up exciting opportunities that redefine the landscape of structural design automation. Looking ahead, researchers have a multitude of opportunities to explore, shaping the future direction in this field. The future opportunities can be summarized as follows:

(1) The integration of cutting-edge DL methods into structural design represents a significant advancement beyond traditional rule-based approaches. These data-driven methods offer superior performance in managing the complexities and multitude of variables inherent in structural design problems. Moreover, these techniques demonstrate enhanced capability in learning from the past experiences of structural engineers, which can hardly be modeled through traditional methods. Future research can also explore the use of physics-informed AI to enable more reliable efficient design process [68,69,73].

(2) Broaden the applications to more design steps and design objects. The current scope of structural design, while impactful, represents only a fraction of the entire design process. There are numerous aspects that remain to be fully automated. Regarding data, augmentation methods might address the limited availability of data and enhance data quality. Developing more effective techniques for extracting precise information from structural drawings and non-textual details in regulatory documents is also vital. In terms of design optimization, given the availability of computational power in structural design, advanced techniques should be employed to optimize the numerous parameters involved in a design project.

(3) Combining flexible AI tools with existing software can reduce computational costs and increase processing speeds by transitioning operations to cloud-based platforms [133]. Cloud-based AI applications support the integration of various AI models, which can be customized and merged according to specific phases of the design process. This flexibility allows engineers to deploy the most effective tools at different stages, eliminating the need for frequent software updates or hardware upgrades. The ability to collaborate across different models streamlines the process from initial design concepts to final compliance check, optimizing the entire workflow.

(4) Implementing systems that offer real-time design guidance can accelerate the design process by providing immediate feedback. By leveraging historical design data, AI can assist engineers with insights derived from similar past projects. This knowledge not only informs current design efforts with proven solutions and techniques but also aids in error detection. Such systems continuously analyze and refine designs throughout their development, ensuring they meet regulatory standards. This approach not only accelerates the design phase but also minimizes errors and subsequent rework, thereby optimizing project timelines and cutting costs.

(5) The effective deployment of AI in structural design not only requires robust technology but also a workforce that is skilled in utilizing such tools. Developing collaborative interfaces that facilitate direct interaction between engineers and AI systems can streamline the design process [134]. Human-AI collaboration can also help in other structural design processes, such as using LLM to automated structural analysis including finite element modeling [135], including LLM as the core interactive control [91]. This approach not only speeds up the design process but also ensures that the outputs are more accurate and aligned with human expertise and industry standards. Furthermore, such collaborative tools can assist in training and guiding engineers, gradually enhancing their proficiency with AI technologies. This ongoing interaction between human intelligence and AI fosters a productive relationship that can lead to more innovative solutions and a higher degree of customization in structural designs.

(6) Full-process automation is an emerging direction in structural engineering. It involves the automatic floor plan analysis [130] and integration of automated structural design with automated construction methods. For example, floor plan analysis can include segmenting walls [136,137] to prepare data for downstream structural design. AI-generated designs can be directly linked to construction technologies such as automated formwork layout systems [138], 3D printing [139] or robotic assembly. Automating both design and construction could lead to higher efficiency, lower labor costs, and fewer errors. However, realizing this goal requires collaboration among structural engineers, AI developers, and construction experts. Future research can focus on aligning design outputs with automated construction systems to improve the overall workflow.

CRediT authorship contribution statement

Hao Xie: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Qipei Mei:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization. **Ying Hei Chui:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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