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GENERATIVE ARTIFICIAL INTELLIGENCE MODELS APPLIED TO STEEL STRUCTURES: A SYSTEMATIC LITERATURE REVIEW

MODELOS DE INTELIGÊNCIA ARTIFICIAL GENERATIVA APLICADOS ÀS ESTRUTURAS DE AÇO: UMA REVISÃO SISTEMÁTICA DA LITERATURA

MODELOS DE INTELIGENCIA ARTIFICIAL GENERATIVA APLICADOS A LAS ESTRUCTURAS DE ACERO: UNA REVISIÓN SISTEMÁTICA DE LA LITERATURA

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ABSTRACT
The growing interest in automating structural design has driven the application of generative artificial intelligence models to tasks such as layout generation and automated design documentation. However, despite recent scientific advances, steel structures remain an underexplored field, with no consolidated systematic review mapping the architectures employed, the tasks addressed, and the persistent gaps in this specific domain. This work aims to conduct a systematic literature review on the application of generative AI models to steel structure design, carried out according to the protocol of Kitchenham (2004) and Kitchenham and Charters (2007). The databases consulted were IEEE Xplore, ScienceDirect, Scopus, SpringerLink, and the CAPES Journal Portal, covering publications from 2019 to April 30, 2026. A total of 895 articles were initially identified, resulting in 12 studies included after application of eligibility and quality criteria. Results reveal a still incipient scientific production concentrated in steel structural layout generation, with a marked scarcity of studies addressing the broader steel structure domain. It is concluded that the field requires deeper exploration of structural typologies, steel connection morphologies, and the incorporation of design specifications into synthetic outputs.

KEYWORDS: *Generative Artificial Intelligence. Steel Structures. Systematic Review. Generative Models. Structural Engineering.*

RESUMO
O crescente interesse na automação do processo em projetos estruturais impulsionou a aplicação de modelos de inteligência artificial generativa, a tarefas como geração de *layouts*, apoio à documentação técnica e síntese de artefatos de projeto. Todavia, apesar do avanço científico observado nos últimos anos, as estruturas de aço configuram um campo ainda pouco explorado, inexistindo uma revisão sistemática consolidada que mapeie as arquiteturas empregadas, as tarefas abordadas e as lacunas persistentes nesse domínio específico. Este trabalho tem como objetivo realizar uma revisão sistemática da literatura sobre a aplicação de modelos generativos de inteligência artificial ao projeto de estruturas de aço, conduzida segundo o protocolo de Kitchenham (2004) e Kitchenham e Charters (2007). As bases consultadas foram IEEE Xplore, ScienceDirect, Scopus, SpringerLink e o Portal de Periódicos CAPES, com recorte temporal de 2019 a 30 de abril de 2026. 895 artigos foram identificados inicialmente, resultando em 12 estudos incluídos após aplicação dos critérios de elegibilidade e qualidade. Os resultados evidenciam uma produção científica ainda incipiente e concentrada na tarefa de geração de *layouts*, com escassez expressiva de estudos focados no domínio das estruturas de aço de maneira ampla. Conclui-se que o campo

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carece de uma exploração mais aprofundada de tipologias estruturais, morfologia das conexões estruturais metálicas e incorporação de especificações nos produtos sintéticos.

PALAVRAS-CHAVE: Inteligência Artificial Generativa. Estruturas de Aço. Revisão Sistemática. Modelos Generativos. Engenharia Estrutural.

RESUMEN
El creciente interés en la automatización del proceso de diseño estructural ha impulsado la aplicación de modelos de inteligencia artificial generativa a tareas como la generación de layouts y la documentación automatizada de proyectos. Sin embargo, a pesar de los recientes avances científicos, las estructuras de acero siguen siendo un campo poco explorado, sin una revisión sistemática consolidada que mapee las arquitecturas empleadas, las tareas abordadas y las lagunas persistentes en este dominio específico. Este trabajo tiene como objetivo realizar una revisión sistemática de la literatura sobre la aplicación de modelos generativos de inteligencia artificial al campo de las estructuras de acero, llevada a cabo según el protocolo de Kitchenham (2004) y Kitchenham y Charters (2007). Las bases consultadas fueron IEEE Xplore, ScienceDirect, Scopus, SpringerLink y el Portal de Periódicos CAPES, con un recorte temporal de 2019 a 30 abril de 2026. Un total de 895 artículos fueron identificados inicialmente, resultando en 12 estudios incluidos tras la aplicación de los criterios de elegibilidad y calidad. Los resultados revelan una producción científica aún incipiente, concentrada en la generación de layouts de sistemas estructurales de acero, con una marcada escasez de estudios que aborden el campo de las estructuras de acero en mayor amplitud. Se concluye que el campo requiere una exploración más profunda de las tipologías estructurales, las morfologías de conexiones metálicas y la incorporación de especificaciones de proyecto en los productos sintéticos.

PALABRAS CLAVE: *Inteligencia Artificial Generativa. Estructuras de Acero. Revisión Sistemática. Modelos Generativos. Ingeniería Estructural.*

1. INTRODUCTION

The construction industry constitutes one of the most economically significant sectors for national development, accounting for a substantial share of gross domestic product and employment generation. Within the domain of industrial buildings and infrastructure works, steel structures are widely adopted in warehouses, bridges, footbridges, and multi-story buildings, forming a segment in which delays and rework carry considerable economic impact.

In this context, the automation of tasks in the steel structure design process has become an increasingly active subject of scientific investigation. Rule-based approaches, heuristic optimization, and, more recently, deep learning have been proposed with the aim of reducing human effort in repetitive tasks and expanding the solution space under exploration. Among these approaches, generative artificial intelligence models have emerged as one of the most active frontiers, demonstrating the capacity to synthesize structured content.

In the specific domain of steel structures, the application of generative models holds potential across a range of tasks, including the automated generation of structural steel system layouts, the design of structural connections, and the synthesis of detailed construction drawings, among others.

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The breadth of these applications and the rapid growth of scientific output around generative models position steel structure as a field of significant and yet largely untapped potential.

However, despite the recent scientific advances, a consolidated systematic review that comprehensively maps the architectures employed, the steel structure design tasks addressed, and the persistent gaps in this field remains absent. This gap hinders the guidance of new research efforts, the identification of unexplored opportunities, and the consolidation of knowledge produced in fragmented form across different research groups.

In this context, the present study aims to conduct a systematic literature review on the application of generative artificial intelligence models to steel structure design, mapping the predominant architectures, the tasks addressed, the reported results, and the identified limitations, with a view to consolidating the state of the art and defining the future research agenda in this field.

To achieve this overarching objective, three specific objectives are established: the identification and classification of generative AI model architectures applied to steel structures in the literature from 2019 to April 30, 2026; the characterization of applications and tasks addressed by generative models in this domain; and the identification of persistent gaps and future research opportunities emerging from the analysis of the reviewed corpus.

To this end, a systematic literature review was conducted following the Kitchenham (2004) and Kitchenham and Charters (2007) protocol, with searches carried out across five electronic databases covering the period from 2019 to April 30, 2026, resulting in 12 studies included after eligibility and quality assessment.

2. THEORETICAL FRAMEWORK

The application of artificial intelligence to steel structure design predates the emergence of generative models, having originated with approaches based on expert systems, genetic algorithms, and, more recently, generative artificial neural networks.

For the purposes of this review, only generative models oriented toward the synthesis of visual and geometric representations are considered, excluding large language models (LLMs). In structural engineering, design artifacts (layouts, connection drawings etc.) are fundamentally geometric rather than linguistic in nature. Consistent with this characteristic, broad reviews of generative AI applied to structural design have not identified LLM-based approaches as a relevant paradigm in this domain (AZIZ et al., 2025; LIAO et al., 2024). Within this scope, generative models can be organized into three main families, described as follows.

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Generative Adversarial Networks (GANs)

Proposed by Goodfellow *et al.* (2014), Generative Adversarial Networks (GANs) are an architecture grounded in game theory that leverages the competition between two models as a mechanism for producing new samples, referred to as synthetic outputs. Their architecture comprises two models, a generator and a discriminator, specialized, respectively, in producing new samples and in distinguishing real samples from synthetic ones. Adversarial training drives the generator to produce samples that are progressively less distinguishable from real data.

GANs are a widely adopted architecture for image and synthetic data generation, primarily due to their comparatively simpler architecture relative to other approaches and, consequently, their lower computational training cost.

Diffusion models

Diffusion models are a class of artificial neural network models that incorporate the diffusion theory proposed by Ho, Jain, and Abbeel (2020), or extensions thereof, such as flow models. Diffusion models operate in two stages: a forward process, in which input data are progressively corrupted through the addition of Gaussian noise, and a reverse process, in which the model learns to iteratively undo this corruption. Once trained, the reverse process can be initiated from pure noise sampled from the Gaussian distribution, enabling the generation of new examples that follow the distribution of the original data.

Compared to GANs, diffusion models demonstrate superior performance in preserving fine-grained details, such as textual elements and lines, a characteristic of fundamental importance for applications involving engineering technical drawings. However, the samples generated by these models consist predominantly of rasterized (pixel-based) images, which represents a significant barrier to their adoption in engineering contexts, given that design representations are, for the most part, expressed as three-dimensional models or vector-based compositions.

Graph Neural Networks (GNNs)

Graph Neural Networks (GNNs) are architectures specialized in processing data structured as graphs. Although less commonly employed as generative models, GNNs exhibit strong synergy with structural design applications, given that their topology is particularly well-suited for structural representation: nodes represent structural elements, and edges represent the relationships between them (Wu *et al.*, 2020).

3. METHODOLOGY

This study is characterized as a systematic literature review, conducted in accordance with

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the guidelines established by Kitchenham (2004) and Kitchenham and Charters (2007). The protocol was structured around previously defined research questions, with explicit inclusion, exclusion, and quality criteria, ensuring reproducibility and bias control throughout the study selection process.

3.1. Research Questions

The research questions (RQs) were formulated based on the identification of the gaps described in Section 1 and guide all subsequent stages of the review:

RQ1 What generative artificial intelligence model architectures have been applied to steel structures in the period from 2019 to April 30, 2026?

RQ2 What applications of generative artificial intelligence models have been identified in the field of steel structures?

RQ3 What research gaps and limitations are identified from the analysis of the reviewed corpus?

3.2. Search strings

The search strings were derived from the decomposition of the research questions into terms and synonyms, as presented in Table 1.

Table 1. Terms and synonyms arising from the research questions

Concept	Terms and synonyms
Generative Models	“generative model”,“generative adversarial network”, “GAN”, “diffusion model”, “graph neural network”, “GNN”
Steel Structure	“steel structure”, “structural steel”, “steel frame”, “steel connection”, “steel joint”, “bolted connection”, “welded connection”, "structural connection components",

The resulting search string, adapted for each database, was:

("generative adversarial network" OR "GAN" OR "diffusion model" OR "graph neural network" OR "GNN" OR "generative design" OR "generative model") AND ("steel structure" OR "steel connection" OR "steel frame" OR "steel joint" OR "bolted connection" OR "welded connection" OR "structural steel" OR "structural connection components")

3.3. Databases consulted

The searches were conducted in the following electronic databases, selected for their relevance to the fields of civil engineering and artificial intelligence:

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1. IEEE Xplore Digital Library;
2. ScienceDirect (Elsevier);
3. Scopus (Elsevier);
4. SpringerLink;
5. CAPES Periodicals Portal.

The searches were executed on April 30, 2026, with a temporal scope restricted to the period from January 2019 to April 30, 2026, with no language restriction applied during initial retrieval. The delimitation from 2019 onward is grounded in the consolidation of generative models as a paradigm for applied research, driven by the proliferation of specific GAN architectures, such as StyleGAN (Karras; Laine; Aila, 2018) and BigGAN (Brock; Donahue; Simonyan, 2018), and diffusion models in 2020 (Ho; Jain; Abbeel, 2020).This is consistent with Aziz *et al.* (2025), whose review identifies the year 2020 as the period of emergence of AI applications in structural engineering, noting that prior output was concentrated in approaches based on expert systems and evolutionary algorithms, paradigms distinct from the generative models that constitute the subject of the present review.

3.4. Inclusion and exclusion criteria

The eligibility criteria were defined *a priori*, in accordance with the Kitchenham protocol, and applied in two sequential stages: screening by title and abstract, followed by full-text assessment.

Inclusion Criteria:

IC1 Articles published between January 2019 and April 30, 2026;

IC2 Written in English or Portuguese;

IC3 Articles that propose, implement, or evaluate generative artificial intelligence models applied to the field of steel structures;

IC4 Available in full text through the consulted databases or via the CAPES Periodicals Portal.

Exclusion Criteria:

EC1 Articles duplicated across databases (the occurrence from the database of greatest relevance is retained);

EC2 Articles without peer review (preprints without a published version, technical reports, conference abstracts without a full paper);

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EC3 Articles that apply generative AI exclusively to concrete, masonry, or other non-structural-steel structures, including composite structures in which the steel component is not predominant;

EC4 Articles that apply AI exclusively to structural analysis tasks, load prediction, inspection, or maintenance, with no generative component directed at the field of steel structures;

EC5 Review articles, meta-analyses, or systematic mapping studies on the same subject;

EC6 Articles for which full-text access could not be obtained through the CAPES Periodicals Portal;

EC7 Articles constituting redundant publications: works by the same group of authors reporting the same method and set of results in different journals. Such articles were counted only once, retaining the original publication.

3.5. Quality criteria

To estimate the methodological rigor of the included studies, a quality assessment instrument comprising three criteria was applied, inspired by the QATSDD tool (Sirriyeh *et al.,* 2012) and adapted to the technical context of computational engineering. Each criterion is scored according to the following scale: 1.0 (fully met), 0.5 (partially met), and 0.0 (not met). Studies with a total score below 1.5 were excluded from the synthesis.

Table 2. Quality criteria and scoring

Crit.	Description	Score
QC1	Are the study objective and the design task addressed clearly defined?	0.0 / 0.5 / 1.0
QC2	Is the generative model architecture described in sufficient detail to allow replication?	0.0 / 0.5 / 1.0
QC3	Are the data used for training and evaluation described (source, size, and characteristics)?	0.0 / 0.5 / 1.0
Inclusion threshold		**1,5**

3.6. Screening and selection process

The screening of studies was conducted in two independent rounds by both authors, with disagreements resolved by consensus. Inter-rater agreement was calculated using Cohen's Kappa

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coefficient, with a threshold of $k > 0.85$ adopted as indicative of substantial agreement, in accordance with the recommendation of Kitchenham and Charters (2007).

Table 3. Screening results by database

Database	Retrieved	After Title/Abstract	Full Text	Included
IEEE Xplore	13	0	0	0
Scopus	80	17	12	11
ScienceDirect	787	3	1	1
SpringerLink	4	0	0	0
Portal CAPES	62	0	0	0
Duplicates removed	-51			—
Total	895	20	13	12

4. RESULTS AND DISCUSSION

The lack of eligible studies in IEEE Xplore, SpringerLink, and the CAPES Periodicals Portal reflects the emergent stage of the field, rather than a lack of adjacent scientific output. Liao *et al.* (2024), in a broad-scope review of generative AI applied to structural engineering, identified only one study (FrameGAN) focused on steel structures, with the remaining output concentrated in concrete systems. This finding demonstrates that the scarcity of studies on steel structures does not stem from a thematic choice on the part of the reviewing community, but from the actual state of the literature, a condition that both justifies and motivates the present review.

In terms of geographical origin, all included studies originate from Chinese institutions, reflecting China's leading position in the scientific production on the automation of structural design using generative artificial intelligence. The studies are concentrated in the journals *Engineering Structures*, *Automation in Construction*, *Advanced Engineering Informatics*, and *Journal of Building Engineering*. Table 4 presents the descriptive synthesis of included studies; Table 5 presents the task category assigned to each study.

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Table 4. Descriptive synthesis of included studies

Author(s)	Year	Journal	Main Findings
Fu, Gao e Wang	2023	*Automation in Construction*	Automated generation of steel portal frame (FrameGAN) layouts with performance comparable to that of senior structural engineers.
Du *et al.*	2023	*Applied Intelligence*	Generation of 3D solid models of tubular steel joints with mechanical properties superior to reference solutions.
Fu, Wang e Gao	2024	*Journal of Building Engineering*	Incorporation of physical design rules into adversarial training, with improvements in visual and structural performance over the original FrameGAN.
Li *et al.*	2025	*Engineering Structures*	Latent diffusion model outperforms GANs in layout generation, within an integrated platform for structural design, modeling, and analysis.
Han *et al.*	2025	*Advanced Engineering Informatics*	Generation of new spatial connections with a 20% reduction in mass and improvements in displacement and equivalent stress.
Mou, Chen e Fu	2025	*Engineering Structures*	Synthetic data generation for machine learning training with improved compressive strength prediction of bolted columns
Yu, Li, Xie	2025	*Journal of Constructional Steel Research*	GAN-generated synthetic data enhances neural network performance in ultra-low-cycle fatigue life prediction
Author(s)	**Year**	**Journal**	**Main Findings**
Lu *et al.*	2025	*Ocean Engineering*	CGAN+CNN framework improves fatigue life prediction in welded joints of steel bridges under scarce data conditions

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Wu *et al.*	2025	*Construction and Building Materials*	CTGAN-XGBoost model achieves R^2 = 0.907 in recovery stress prediction of steel shape memory alloys.
Gao *et al.*	2025	*Structures*	GAN-Mix-up augmentation method improves XGBoost generalization in compressive strength prediction of corroded steel tubes.
Zuo *et al.*	2026	*Advanced Engineering Informatics*	Physics-informed data augmentation framework enhances ultimate load prediction with integration into the Rhino-Grasshopper platform.
Zhao *et al.*	2023	*Journal of Building Engineering*	Data-driven method for beam layout generation with performance comparable to that of structural engineers in open-plan structures.

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Table 5. Task Category classification of included studies

Author(s)	Year	Journal	Architecture	Task
Fu, Gao e Wang	2023	*Automation in Construction*	GAN	Layout Generation
Du *et al.*	2023	*Applied Intelligence*	GAN	Connector Generation
Fu, Wang e Gao	2024	*Journal of Building Engineering*	GAN	Layout Generation
Li *et al.*	2025	*Engineering Structures*	Diffusion	Layout Generation
Han *et al.*	2025	*Advanced Engineering Informatics*	GAN	Connector Generation
Mou, Chen e Fu	2025	*Engineering Structures*	GAN	Data Augmentation
Yu, Li, Xie	2025	*Journal of Constructional Steel Research*	GAN	Data Augmentation
Lu *et al.*	2025	*Ocean Engineering*	GAN	Data Augmentation
Wu *et al.*	2025	*Construction and Building Materials*	GAN	Data Augmentation
Gao *et al.*	2025	*Structures*	GAN	Data Augmentation
Zuo *et al.*	2026	*Advanced Engineering Informatics*	GAN	Data Augmentation
Zhao *et al.*	2023	*Journal of Building Engineering*	GNN	Layout Generation

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4.1. RQ1 — Predominant generative model architectures

The analysis of the included studies reveals the predominance of Generative Adversarial Networks (GANs) as the dominant architecture throughout the reviewed period. This prevalence is consistent with the technological maturity cycle of generative models, of which one of the earliest was proposed by Goodfellow *et al.* (2014).

In this context, GAN-based architectures have consolidated as the predominant approach, present in 83.33% of the studies identified in this review. The proposal of FrameGAN by Fu, Gao, and Wang (2023) represents a milestone in this trajectory, employing GANs for the automated layout design of braced steel frames and demonstrating results comparable to those produced by experienced structural engineers. Subsequent variations, such as FrameGAN v2 by Fu, Wang, and Gao (2024), constitute extensions of this same model.

In contrast, diffusion model-based architectures remain incipient in the field of steel structures, exhibiting low adoption among the mapped studies. This limited adoption may be partly attributable to the inherent computational cost of the training and generation processes associated with these architectures. However, their application to steel structural design presents itself as a viable alternative for improving detail quality in design outputs, as exemplified by FrameDiffusion (Li *et al.*, 2025), a diffusion-based variant of the FrameGAN model. A similar situation is observed with GNN-based models, represented by only a single study in this review, which indicates a gap yet to be explored.

4.2. RQ2 — Tasks addressed

The analysis of the included studies allowed the identification of three categories of tasks[3] within the steel structure design process that have been addressed by generative models. The distribution of these tasks across the reviewed corpus is illustrated in Figure 1.

[3] All studies included in this review address a single design task, reflecting the standard specialization of generative AI publications, in which a model is proposed, trained, and evaluated for one specific problem. No study in the corpus addressed more than one task category simultaneously.

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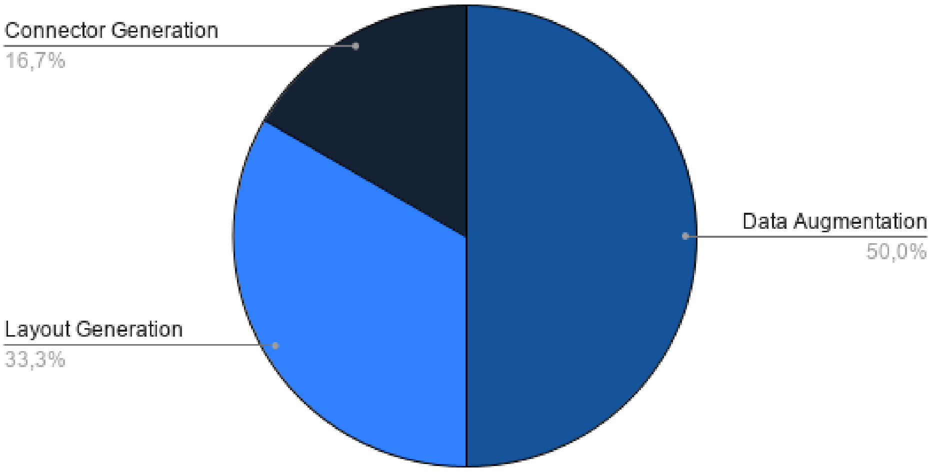
Figure 1. Distribution of tasks addressed by the reviewed studies: 50% data augmentation (dark blue), 33.3% layout generation (blue), and 16.7% connection generation (black)



Generation of Steel Structural System Layouts

The automated generation of steel frame and structural system layouts constitutes the most frequently addressed task in studies on steel structures. In this category, generative models aim to reproduce structural design floor plans. To achieve this goal, the model receives a base floor plan as input and is expected to produce as output the arrangement of structural elements, columns, beams, and steel bracing systems. The works of Fu, Gao, and Wang (2023), Fu, Wang, and Gao (2024), and Li *et al.* (2025) are representative of this category, with a focus on steel frame floor plans.

The reported results indicate that the models are capable of generating structurally plausible layouts according to general design criteria, but exhibit difficulties in incorporating comprehensive normative constraints. Fu, Wang, and Gao (2024) advanced in this direction by proposing the incorporation of physical rules directly into the adversarial training process, reducing the generation of invalid solutions, though without fully eliminating configurations that fail specific code-compliance verifications.

Design and synthesis of steel structural connections

The design of structural connections represents the category of greatest technical complexity and singularity within the steel structure design process, despite accounting for the relatively smallest share of studies in the reviewed corpus (16.67%). It is also the task most directly related to the productive bottleneck identified in the steel structures literature.

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The approach to generating steel structural connections follows the methodology established by Du *et al.* (2023) for the generation of spatial connections. The authors proposed a methodology in which a training database of point clouds derived from topologically optimized connections was assembled and supplied to a GAN-based generative model for the synthesis of new samples. Through this approach, the authors were able to synthesize novel three-dimensional models of spherical connections that are more structurally efficient than those present in the training database. Similarly, Han *et al.* (2025) developed the ConnectorGEN model in accordance with the approach proposed by Du *et al.* (2023), targeting the generation of tubular spatial connections in steel structures.

Synthetic data generation

Although synthetic data generation does not represent an application exclusive to steel structures, it accounts for 50% of the studies identified in this review. This task assumes a secondary role within the studies, serving the purpose of preparing data for the validation or training of other models or numerical methods. The popularity of this approach may be attributable to the considerable scarcity of data in the engineering domain, which necessitates techniques capable of enriching input datasets in order to enable more robust analyses and results.

4.3. RQ3 — Identified limitations and research gaps

The analysis of the limitations reported by the included studies allowed the identification of two groups of recurring problems, described as follows.

Knowledge Representation

Structural steel design, like other engineering design disciplines, is represented through two distinct and complementary channels: geometry and specifications. Geometry communicates the dimensional aspect of the structural solution, for example, the beam web depth, while specifications communicate the constructive aspect, for example, the bolt hole pattern layout. Both components are necessary for the fulfillment of the structural design, and their omission is inadmissible.

Thus, both layout generation and connection generation fail to represent the specifications component, limiting themselves exclusively to the generation of geometry or structural arrangements. This is particularly critical in the steel structural connections generation, given that specifications constitute the critical design component, the product of physical, normative, and constructive constraints. The disregard for this component likely renders the synthetic connections inapplicable in engineering practice, distancing generative models from real-world steel structure design.

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Scarcity of Structural Typologies

Despite the relevance of the aforementioned studies, a mismatch is observed between the typological scope adopted in the literature and the actual composition of the steel structures field. The studies conducted by Fu, Gao, and Wang (2023), Fu, Wang, and Gao (2024), and Li *et al.* (2025) address exclusively the frame typology, disregarding structural types of greater prevalence in steel construction, such as industrial, offshore, and marine structures. Similarly, the generation of steel structural connections has been concentrated on 3D models of spatial connections which, although common, do not adequately represent the full breadth and diversity of existing structural connections. For instance, beam-to-column connections, beam splices, and base plates were not explored by the methodology proposed by Du *et al.* (2023), which is, furthermore, ill-suited for representing this broad category of connections.

Consequently, in both cases addressed, the thematic concentration compromises the generalizability of the developed models and limits the findings relevance to the field of steel structures in its full scope.

5. CONCLUDING REMARKS

The present study conducted a systematic literature review on the application of generative artificial intelligence models to steel structure design, covering publications from 2019 to April 2026. The review was conducted in accordance with the protocol established by Kitchenham and Charters (2007), with searches performed across five electronic databases, yielding 12 included studies after application of the eligibility criteria and methodological quality assessment.

In response to RQ1, it was found that Generative Adversarial Networks (GANs) constitute the predominant architectural family in the reviewed corpus, accounting for 83.33% of the studies, with incipient presence of other architectures such as diffusion models and GNNs.

In response to RQ2, three task categories were identified: structural layout generation (33.33%), connection design (16.67%), and synthetic data generation for training set augmentation (50%). The larger proportion of studies focused on data augmentation exposes the scarcity of available data in the steel structures field. Furthermore, the generative tasks are variations of the same models, FrameGAN (Fu; Gao; Wang, 2023) and 3D-JointGAN (Du et al., 2023). In addition, layout generation studies were concentrated on steel frame floor plans, with a notable scarcity of studies addressing industrial steel structures and connections, while connection generation was focused on 3D models of spatial connections. Moreover, in both cases, the synthesized outputs do not incorporate design specifications, distancing them from real-world engineering practice.

In response to RQ3, two recurring groups of limitations were identified across the reviewed studies: (i) concentration on steel frame floor plans, with limited coverage of other structural

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typologies; and (ii) constraints in generation to geometric characteristics only, omitting design specifications.

Limitations of this review

The present study presents limitations inherent to the adopted method. The restriction of language to English and Portuguese, while necessary for quality control purposes, may have resulted in the exclusion of relevant studies published in other languages.

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