Journal of Industrial Engineering and Applied Science
Vol. 4, No. 1, 2026 | ISSN 3005-6071 (Print) | ISSN 3005-608X (Online) | CODEN: JIEAAE

A Review of the Development of Automated Metal Parts Modeling and Management Technologies Based on BIM and Artificial Intelligence

LI, Zhuoxuan [1*]

[1] Suzhou University of Science and Technology, China

**** LI, Zhuoxuan is the corresponding author, E-mail: Coriander041114@outlook.com***

Abstract: Metal components, due to their high prefabrication rate and discrete manufacturing characteristics, have become an ideal carrier for verifying intelligent construction technologies. However, traditional modeling methods face bottlenecks such as low efficiency, poor robustness, and semantic gaps. This study systematically reviews the research progress of Building Information Modeling (BIM) and Artificial Intelligence (AI) in the automated modeling and life-cycle management of metal components. First, it elucidates the semantic support for metal structures in the IFC 4.3 standard and the theoretical basis of BIM-AI integration. Then, from a forward design perspective, it reviews parametric modeling, deep learning topology optimization, and generative adversarial networks (GANs), while from a reverse reconstruction perspective, it outlines point cloud semantic segmentation and Scan-to-BIM automation technologies. Further, it explores intelligent management methods such as knowledge graph compliance checks, digital twin frameworks, and visual defect detection. Finally, it points out key challenges and future development directions, including data heterogeneity, scarce annotations, and interpretability.

Keywords: Building Information Modeling, Artificial Intelligence, Metal Components, Point Cloud Semantic Segmentation, Scan-to-BIM.

Disciplines: Artificial Intelligence Technology. **Subjects:** Machine Learning.

DOI: https://doi.org/10.70393/6a69656173.333839 **ARK:** https://n2t.net/ark:/40704/JIEAS.v4n1a02

1 INTRODUCTION

1.1 BACKGROUND OF INTELLIGENT CONSTRUCTION FOR METAL STRUCTURES

Intelligent construction is gradually reshaping the traditional engineering delivery model. The core of this paradigm shift lies in mapping the construction process of the physical world onto a digital twin system, thereby realizing the evolution from fragmented project management to integrated product manufacturing [1]. In this macro context, metal structures—encompassing steel structures, complex MEP (mechanical, electrical, and piping) systems, and precision nodes—have become the best material carrier for verifying the theory of intelligent construction due to their inherent "high prefabrication rate" and "discrete manufacturing" attributes. Unlike on-site cast concrete structures, the production logic of metal components is closer to that of precision manufacturing, requiring millimeter-level processing accuracy at the factory level and transportation to the site for zero-error assembly via a complex supply chain network [2]. This characteristic renders metal structural engineering more conducive to seamless digital integration for deep integration with digital technologies (such as BIM).

However, as modern infrastructure develops towards large-scale and irregular shapes, the engineering management of metal components is facing the dual challenges of geometric shape and semantic information. At the geometric level, large-span spatial steel structures or free-form curtain walls often involve tens of thousands of non-standard components. Their topological complexity and geometric entropy far exceed those of traditional regular buildings, causing the traditional expression method based on two-dimensional drawings to completely fail, and parametric and automated means are urgently needed [3]. At the semantic level, the entire life cycle of metal components spans multiple heterogeneous links such as design, manufacturing (CAM), logistics and installation, and there has long been a "data silo" phenomenon between each link. Although Building Information Modeling (BIM) is regarded as the core carrier of engineering data, in practical applications, the design model (Design BIM) is often difficult to directly guide CNC machining, and the completed physical structure lacks real-time synchronization with the digital model [4].

Currently, the common pain point faced by the engineering community is that a large number of existing metal structures or construction site components are still in an "offline" state, lacking efficient reverse digitization means. Traditional laser scanning post-processing relies heavily on manual model making, which is inefficient and prone to cognitive bias. Therefore, how to use high-precision point cloud data obtained by LiDAR and combine it with computer vision algorithms of artificial intelligence (AI) to realize the automated reconstruction of metal components from "discrete point cloud" to "semantic entity" (Scan-to-BIM) has become a key bottleneck connecting the physical world and the digital foundation [5]. This is not only a prerequisite for realizing automated inspection of engineering quality, but also an inevitable path to intelligent operation and maintenance throughout the entire life cycle.

1.2 Current Status and Limitations of Traditional Modeling Methods

Although Building Information Modeling (BIM) has been established as the standard ontology for digital engineering delivery, the industry is still hampered by the "labor-intensive" work mode in the modeling practice of high-precision metal components. Especially in the scenarios of existing industrial facility renovation and large steel structure construction management, the current "Scan-to-BIM" process is still essentially still within the scope of "manual drawing" in the face of massive point cloud data collected by LiDAR. The empirical study of Volk et al. [6] pointed out that in the reverse reconstruction process, non-creative tasks such as data cleaning and feature extraction account for the majority of the processing time. This high dependence on human experience inevitably introduces random cognitive errors, resulting in significant geometric consistency deviations in the reconstruction results of the same set of data in the hands of different engineers, which makes it difficult to meet the stringent accuracy requirements of industrial-grade digital twins.

At the level of physical feature recognition, the unique optical properties of metal materials have become an insurmountable obstacle for automated algorithms. Wang and Kim [7] analyzed in their long-term review that the high specular reflection effect commonly found on metal surfaces leads to multipath propagation of laser ranging signals, resulting in a large number of "outliers" and "false ghosts" in the original point cloud. Traditional primitive fitting algorithms—such as Hough transform or RANSAC and its variants—are extremely unrobust when dealing with such high-noise, non-Lambertian surface data. In addition, industrial-grade metal components (such as pipeline systems with flanges, valves and stiffeners) often exhibit extreme complexity and irregularity in their topology. Patraucean et al. [10] emphasized that existing commercial reverse engineering software mainly relies on predefined simple geometry libraries (such as cylinders and cuboids) for matching. Once encountering irregular steel components or non-standard connection nodes, rule-based algorithms fail, forcing engineers to revert to the inefficient path of manual polygon mesh editing.

The more fundamental academic pain point lies in the "geometric-semantic gap." The core demand of engineering management is not simply three-dimensional visualization, but logical reasoning about the functional attributes and topological relationships of components. Pauwels et al. [8] criticized that current reverse modeling techniques focus more on surface reconstruction of geometric shapes, and the generated models are often a bunch of meaningless "dead geometries," lacking key semantic information such as material properties, connection relationships, and fluid direction. This semantic deficiency directly leads to the model being unable to be read by structural analysis software (FEM) or numerical control machining equipment (CNC). Czerniawski and Leite [9] further added that although some automated plugins attempt to recover semantics through rule-based reasoning, when faced with severe occlusion and component clutter, the hard-coded rules-based method lacks the ability to generalize the understanding of the context and cannot fill in the missing information through "association" like human engineers. In summary, traditional modeling methods face a triple dilemma when dealing with metal components: efficiency bottlenecks, weak noise resistance, and a lack of semantic understanding.

Table 1 summarizes the limitations of current mainstream modeling methods in key dimensions.

Table 1. Comparison of Limitations in Traditional Metal Component Modeling Methods

Dimension	Manual Modeling	Rule-based Automation	Key Limitations
Efficiency	Extremely Low	Medium	Cannot handle massive datasets; high time cost.
Accuracy	High variance	Good for standard shapes only	Fails on irregular/deformed metal parts (e.g., warped beams).
Robustness	High	Low	Algorithms fail due to specular reflections and clutter.
Semantics	Manually enriched	Limited	Objects are geometric shells without engineering logic.
Scalability	Linear	Limited by rule complexity	Hard to adapt to new, complex metal topologies without reprogramming.

1.3 Evolution from Digitization to Intelligence

The integration of BIM and AI is not a simple tool overlay, but a deep symbiotic relationship. Pan and Zhang [11] define this mechanism as "two-way empowerment of data and algorithms": on the one hand, BIM provides AI models with high-quality training samples rich in semantics (such as labeled metal component libraries), solving the "small sample" dilemma faced by AI in the engineering field; on the other hand, AI uses its perception and cognition advantages in computer vision (CV), generative design and natural language processing (NLP) to give BIM models the ability to automatically generate, repair and diagnose. This integration is particularly crucial in the field of metal components. It is no longer limited to single geometric modeling, but attempts to build a "semantic digital twin" with physical perception and logical reasoning capabilities [12].

Based on the above background, this study aims to systematically review the cutting-edge progress of BIM and AI technologies in the automated modeling and full-process management of metal components. This article begins with a theoretical perspective, explaining the compatibility mechanism between the IFC data standard and various AI algorithms in metal structure engineering. It then focuses on two core paradigms of automated modeling: forward derivation design based on parametric rules and generative adversarial networks (GANs), and inverse reconstruction (Scan-to-BIM) technology based on point cloud semantic segmentation and geometric feature fitting. Building on this foundation, the review extends to the level of intelligent management, deeply analyzing knowledge graph-driven compliance checks, BIM-driven CNC machining (CAM), and vision-based defect detection applications. Finally, this study critically analyzes the key challenges of current technologies in terms of data heterogeneity, dataset scarcity, and algorithm interpretability, and provides an outlook on future research directions.

2 THEORETICAL FRAMEWORK OF BIM AND ARTIFICIAL INTELLIGENCE INTEGRATION

2.1 Data Representation Standards for Metal Components

In the digital ecosystem of intelligent construction, the geometry and physical properties of metal components must be mapped into computer-readable structured data. Currently, the latest version of the IFC 4.3 standard (which has been officially adopted as ISO 16739-1:2024) released by the buildingSMART organization is the globally accepted BIM data exchange paradigm [13]. Compared with the previous IFC4 version, this new standard released in 2024 significantly expands the semantic support for the infrastructure field and introduces for the first-time dedicated entities for steel structure bridges and railway systems (such as IfcBridgePart, IfcRail), providing a more complete ontology level for the digital expression of large metal infrastructure.

Unlike the solid representation of concrete structures, metal structure engineering has extremely high semantic requirements for the topological connectivity and fabrication features of components. Under the IFC 4.3 architecture, metal beam and column components are not only instantiated as IfcBeam or IfcColumn, but their complex node connections (such as bolt groups, fillet welds, and splice plates) are further refined and discretely represented through IfcDiscreteAccessory or IfcMechanicalFastener. To describe the complex assembly logic between these components, IFC employs an object-oriented association mechanism based on set theory. According to ISO 16739-1:2024, the connection relationship of metal nodes is implemented through the objectified association entity IfcRelConnects, which binds master and slave components at the semantic level through the RelatingElement and RelatedElement properties [13]. Although the new standard has made breakthroughs in semantic coverage, in the actual data interoperability process, semantic degradation remains an unresolved theoretical problem.

In his study on model exchange for steel structure products, Lipman [14] pointed out that when design models are exported from parametric software (such as Tekla Structures) to IFC format, the original parametric feature construction history (CSG History) – i.e., features generated by stretching and Boolean shearing – often collapses into static boundary representations (B-Rep). This means that a steel pipe node containing bevel information may degenerate into a semantically null mesh (Faceted Brep) containing only triangular facets in the IFC file. This degradation directly hinders the downstream AI algorithm from automatically identifying and reasoning about the processing features of components.

Furthermore, in order to address the limitations of the general IFC standard in specific metal processing scenarios, Model View Definition (MVD) remains an indispensable data filtering mechanism. Venugopal et al. [15] emphasized that a dedicated MVD for steel fabrication needs to strictly define the ontology of data exchange to ensure semantic consistency of micro-properties such as bolt hole diameter and weld grade when transferred between heterogeneous software. Without such rigorous semantic constraints, even when using the latest ISO 16739-1:2024 standard, AI models are still very prone to "garbage in, garbage out" (GIGO) phenomena when reading data.

2.2 Classification of AI Algorithms in Civil Engineering

In the automated modeling and full-process management system of metal components, artificial intelligence algorithms play the role of "computing engine" and are responsible for processing multimodal data from geometric perception to semantic reasoning. According to the modality of data input and the nature of processing tasks, the existing AI technology stack can be methodologically divided into three core schools: geometric perception based on computer vision, generative optimization based on machine learning, and knowledge reasoning based on natural language processing [16].

2.2.1 Computer Vision and Geometric Deep Learning

For steel structure nodes with strong topological connections, graph neural networks (GNNs) demonstrate superior topological reasoning capabilities compared to traditional methods by modeling the components as graphs and passing messages between nodes and edges.

2.2.2 Generative Artificial Intelligence and Optimization

Generative AI methods, including GANs and deep reinforcement learning, enable automated design exploration and assembly planning for metal components [17]. Details are discussed in Chapter 3.

2.2.3 Natural Language Processing for Knowledge Engineering

Metal structure engineering management involves a large amount of unstructured text data, including design codes, construction plans and acceptance records. Natural language processing (NLP) technology aims to break down the semantic barriers between these texts and BIM models. Through named entity recognition (NER) and relation extraction technology, AI can automatically extract constraint rules from standard texts such as the "Steel Structure Design Standard" and convert them into computer-executable logical statements (such as SWRL rules). This process is usually combined with knowledge graph technology to build a domain ontology network covering "component-material-construction method-standard" to support automated compliance checking (ACC). The research of Zhang and El-Gohary [18] shows that NLP algorithms combined with deep learning models (such as BERT) have significantly surpassed the accuracy of traditional keyword matching technology in semantic understanding when dealing with long and difficult sentences and professional terms unique to the engineering field.

3 APPROACHES FOR AUTOMATED FORWARD DESIGN AND GENERATION

3.1 PARAMETRIC MODELING BASED ON RULES AND SCRIPTS

Parametric design, as the initial stage of automation, is based on establishing an explicit logical mapping between geometric parameters and constraint rules. Wortmann and Tunçer [19] define it as a history-based deductive system, which drives the generation of models through a pre-defined algorithm process and has a high degree of determinism.

In industry practice, the application of parametric technology presents a misalignment between "design" and "delivery". Holzer [20]'s empirical investigation points out that although visual scripting tools (such as Grasshopper) are widely used in academia to explore complex forms, in actual engineering delivery, they are often limited to the conceptual stage and have not fully penetrated into the mainstream process of construction drawings and information management. He emphasizes that academia focuses on algorithm innovation, while engineering practice pays more attention to the stability of BIM data and the efficiency of multidisciplinary collaboration.

Nevertheless, in the field of detailed design, rule-based systems have become a key means to solve repetitive modeling. A typical example of this path is to convert design specifications into executable computer code. For example, Eastman et al. [21] pointed out in their research on automated rule checking that rule-based systems are essentially "hard-coding" expert knowledge into a series of If-Then logical statements. Although this method is highly efficient in processing standardized components that conform to preset logic, its inherent defect is that it cannot handle abnormal situations outside the "rule base". Davis [22] further describes it as “topological rigidity”: once the design requirements exceed the preset script framework (for example, changing from a standard I-beam node to an undefined irregular cast steel node), the original parameterized script will often fail directly due to logical breakage and cannot be adaptively adjusted like a human engineer.

3.2 TOPOLOGY OPTIMIZATION DRIVEN BY DEEP LEARNING

In the detailed design stage of metal components, in order to achieve the ultimate balance between material efficiency and mechanical properties, topology optimization (TO) has been widely used in the morphological generation of cast steel nodes and irregular connectors. Traditional topology optimization methods require hundreds of iterative FEA calculations, taking hours to days for complex 3D nodes, which hinders real-time engineering application.

In order to overcome this computational bottleneck, the surrogate model technology based on deep learning has emerged. Its core logic is to reconstruct the topology optimization problem into a nonlinear mapping problem from "boundary conditions and load field" to "optimal density distribution map". Sosnovik and Oseledets [23] first proposed an acceleration framework based on convolutional neural network (CNN). By utilizing a convolutional encoder-decoder architecture with powerful feature extraction and image generation capabilities, the final material layout can be predicted directly based on the initial stress distribution. Experiments show that this method improves the computation speed by two orders of magnitude while ensuring structural compliance, realizing a paradigm shift from "iterative solution" to "end-to-end reasoning".

For the unique three-dimensional solid nodes in metal structures (such as tree branch column nodes or spatial grid ball nodes), two-dimensional image generation algorithms are often not directly applicable. Xiang et al. [24] further extended this technology to three-dimensional voxel space and proposed a deep convolutional neural network (CNN) specifically designed for 3D structural topology optimization. The model adopts a U-Net encoder-decoder architecture and is trained using datasets generated by the Simplified Isotropic Material with Penalization (SIMP) method under randomized loading conditions and volume fractions. Experimental results demonstrate that the trained network can predict near-optimal 3D structures in negligible time without any iterative scheme. Furthermore, the study explored the generalization ability of the proposed method under both single and multiple boundary conditions, showing that the deep learning approach achieves a significant reduction in computational cost with only minimal sacrifice in design performance. This work also extended to stress-based topology optimization for L-shaped design domains, demonstrating the portability of the proposed method to more complex engineering constraints commonly encountered in metal component design.

3.3 Generative Design for Complex Metal Connections

If deep learning-based topology optimization (Section 3.2) aims to find a single "optimal solution," then the core objective of generative design is to explore the "possibility boundary" of the design space. For cast steel nodes or additive manufacturing (3D printing) metal components, design requirements are often non-convex and multi-objective. Traditional parametric methods are limited by "topological rigidity," making it difficult to effectively explore unknown solution spaces. To address this issue, morphological generation algorithms based on generative adversarial networks (GANs) have gradually become a research focus in academia.

Yu et al. [25] proposed a structural generation framework based on conditional generative adversarial networks (cGANs) in their research published in Structural and Multidisciplinary Optimization. The innovation of this method lies in encoding design constraints (such as load locations and support boundaries) as conditional images and inputting them into the generator, while the discriminator is responsible for evaluating whether the generated structural morphology conforms to mechanical logic. The method first trains a CNN-based encoder-decoder network on low-resolution datasets, then employs a two-stage cGAN refinement process to connect pre-trained networks with high-resolution optimized structures. This approach learns the implicit mapping from boundary conditions to structural topology through adversarial training, enabling near-optimal structure prediction with negligible computational time. Experimental results show that the model can generate metal structure configurations with clear boundaries and near-optimal mechanical performance in milliseconds, effectively solving the contradiction between "morphological exploration" and "computational efficiency" in complex node design.

Furthermore, in the industrial customization of metal components, design diversity and aesthetic features are equally important. Oh et al. [26] pointed out in their research published in the Journal of Mechanical Design that simple topology optimization often converges to similar skeleton structures and lacks aesthetic variations. To address this, they proposed an integrated framework called Deep Generative Design (DGD), which uses a variational autoencoder (VAE) to construct a latent space. By performing random sampling or interpolation operations in the latent space, engineers can continuously generate a series of metal component design schemes with different topologies but comparable performance. This approach not only empowers AI with the creativity to "learn by analogy," but also provides designers with a rich 3D candidate model pool, enabling them to perform secondary screening based on manufacturing processes or architectural aesthetic requirements.

4 TECHNOLOGIES FOR AUTOMATED REVERSE RECONSTRUCTION FROM POINT CLOUDS

4.1 Point Cloud Data Acquisition and Preprocessing

In the digital reverse reconstruction of metal components, the acquisition of high-precision three-dimensional point cloud data is the starting point of the entire technology chain. Terrestrial laser scanning (TLS) dominates the acquisition of geometric information of steel structures due to its millimeter-level measurement accuracy and high-speed data acquisition capability [27]. For scanning operations of large steel structures, reasonable path planning directly affects data integrity and efficiency.

The original point cloud usually contains noise and outliers, which need to be preprocessed before it can be used for subsequent analysis. Statistical outlier removal (SOR) is a commonly used denoising method. Its principle is to calculate the average distance from each point to its K nearest neighbors and mark points that deviate significantly from the distribution as outliers for removal. Let the average distance of the K nearest neighbors of point p be $\overline{d_p}$. A point is considered an outlier if its distance exceeds the global mean μ_d plus or minus n times the standard deviation σ_d, shown as formula 1.

$$|\overline{d_p} - \mu_d| > n\sigma_d \quad (1)$$

Registration of multi-site data is another key step. The Iterative Closest Point (ICP) algorithm and its variants are currently the most commonly used fine registration methods, which achieve precise alignment by iteratively optimizing the rigid body transformation parameters between two sets of point clouds [28].

4.2 Deep Learning-Based Point Cloud Semantic Segmentation

Point cloud semantic segmentation aims to assign semantic category labels to each point, which is a key step in Scan-to-BIM automation. Unlike regularized images, point clouds have the characteristics of disorder and non-uniform density distribution, posing unique challenges to the design of deep learning algorithms.

4.2.1 Basic Network Architecture

PointNet was the first to realize the direct processing of raw point clouds [29]. It extracts features point by point by sharing a multilayer perceptron and aggregates global features using max pooling, thus solving the problem of permutation invariance of point clouds. Its core can be represented as formula 2.

$$f(\{x1,\dots,xn\}) = \gamma\,(MAX_{i=1\dots n}\{h(xi)\}) \quad (2)$$

Where h is the pointwise feature transformation and MAX is the symmetric aggregation operation. However, PointNet failed to effectively capture local geometric structures. PointNet++ made up for this limitation by using a hierarchical point set learning framework to recursively extract local features in a multi-scale neighborhood [30].

4.2.2 Large-Scale Point Cloud Processing

In practical engineering, point clouds often reach the scale of millions of points. RandLA-Net uses random sampling instead of computationally intensive farthest point sampling and designs a local feature aggregation module to preserve geometric details, enabling it to process point clouds of the order of 10^5 in a single forward pass, achieving a speed improvement of approximately 200 times compared to traditional methods [31].

In recent years, Point Transformer has introduced a self-attention mechanism into point cloud processing, enabling the network to adaptively focus on the most informative parts and establish long-range dependencies [32]. These advancements have laid the technical foundation for the collaborative recognition of components of different scales in complex steel structure scenes.

Table 2 summarizes the performance of representative methods on the S3DIS indoor scene dataset.

TABLE 2. PERFORMANCE COMPARISON OF METHODS ON THE S3DIS INDOOR SCENE DATASET

Method	Year	Overall Accuracy (OA)	Mean IoU (mIoU)
PointNet [29]	2017	78.62%	47.71%
PointNet++ [30]	2017	Not provided	53.5%
RandLA-Net [31]	2020	88.0%	70.0%
Point Transformer [32]	2021	90.8%	70.4%

4.2.3 Special Applications of Steel Structures

Research on steel structures is gradually increasing. Researchers use BIM software to generate point cloud datasets of steel components and realize the classification and segmentation of components such as beams, columns, and supports based on deep learning [33]. The synthetic point cloud generated from the BIM model is combined with a small amount of real data for training, which can significantly improve the segmentation performance. This is of great value to professional fields that lack labeled data [34].

4.3 Automatic Reconstruction from Point Cloud to BIM Model

4.3.1 Geometric Information Extraction

After semantic segmentation, precise geometric parameters need to be extracted from the component point cloud. The RANSAC algorithm is a classic method for planar primitive detection. It fits candidate planes through random sampling and iterative optimization, and has good robustness to noise [35]. For circular tube components, principal component analysis can be used to determine the principal axis direction, and then the cross section can be extracted along the axis for circular fitting to restore the position, direction, and diameter parameters [36].

4.3.2 Scan-to-BIM Automation

Traditional Scan-to-BIM relies heavily on manual modeling, which is time-consuming and prone to introducing errors. Recently, the open-source tool Cloud2BIM has integrated functions such as wall segmentation and opening detection, and can directly convert point clouds into BIM models that conform to IFC standards. The processing speed can reach 7 times that of similar tools [37].

For steel structures, researchers have proposed a method for automatically identifying structural steel components based on TLS data. Kernel density estimation is used to determine the cross-section shape and matching is performed through a preset cross section library. A cross section recognition rate of 92% was achieved on an experimental steel frame [38]. For spatial grid structures, the spherical node extraction algorithm based on voxelization and RANSAC, as well as the oriented bounding box registration strategy, have been successfully applied to the as-built archiving of actual projects [39].

4.3.3 Quality Inspection and Deformation Monitoring

Virtual trial assembly (VTA) of precast steel components is an important application scenario of point cloud technology. Automated VTA methods based on TLS and BIM include assembly control point extraction and bending torsional deviation detection, which significantly improve efficiency compared to traditional total station measurements [40].

In deformation monitoring, the M3C2 algorithm can directly compare multi-temporal point clouds without generating intermediate grids, demonstrating the advantage of quantitative full-field analysis in the overall deformation detection of bridges [41]. Combined with the multi-scale method of least squares plane fitting, accurate quantification of bridge deck deflection and pier verticality can be achieved simultaneously.

5 INTELLIGENT MANAGEMENT METHOD FOR THE ENTIRE LIFE CYCLE OF METAL COMPONENTS

5.1 KNOWLEDGE GRAPH BASED AUTOMATED COMPLIANCE CHECKING

Metal structure engineering involves a large number of design specifications and construction standards. Traditional manual review methods are inefficient and prone to omissions. Transforming specification clauses into machine-executable logical rules and combining them with BIM models for automated compliance checking (ACC) is an important direction for intelligent management.

Knowledge graph technology provides an effective carrier for this. Entities and relationships are extracted from specification texts through natural language processing to construct a domain ontology network of "component-material-process-standard" [44]. For example, the clause "the flange thickness of H-shaped steel columns is not less than 16mm" can be transformed into a SPARQL query statement, automatically traversing all IfcColumn instances in the BIM model and verifying their geometric properties. The research of Zhang and El-Gohary shows that NLP models based on deep learning (such as BERT) have significantly better semantic understanding accuracy than traditional keyword matching methods when processing professional terms in the engineering field [45].

In practical applications, knowledge graphs can also support change impact analysis. When a node design is modified, the system can automatically identify the affected downstream components and related specification clauses along the associated path, assisting engineers in quickly assessing change risks.

5.2 DIGITAL TWIN FRAMEWORK FOR MANUFACTURING AND ASSEMBLY

The entire process of metal component design and installation involves multiple heterogeneous systems. Traditional information transmission relies on two-dimensional drawings and manual conversion, which easily leads to data gaps. The Digital Twin framework aims to establish a real-time bidirectional mapping between physical entities and digital models, achieving seamless integration of design, manufacturing, and assembly.

In the manufacturing stage, the BIM model needs to be converted into a format recognizable by CNC machining. Geometric expressions in the IFC standard (such as IfcExtrudedAreaSolid) need to be mapped to G-code or STEP-NC instructions [46]. The key challenge in this process is maintaining semantic integrity—ensuring that machining features such as weld bevel angles and bolt hole positioning tolerances are not lost during format conversion.

In the assembly stage, deep reinforcement learning (DRL) is used to solve complex hoisting sequence planning problems. The agent learns the optimal path to avoid collisions through trial-and-error interaction with the BIM environment [47]. Research by Zhou et al. shows that a virtual trial assembly system combined with TLS scanning data can detect more than 95% of geometric interference problems before actual installation, significantly reducing the on-site rework rate [42]. The core value of digital twins lies in closed-loop feedback. Measured data from the construction site (point cloud, sensor readings) are continuously transmitted back to update the digital model, ensuring that it always reflects the true state of the physical entity and providing a reliable data foundation for subsequent operation and maintenance.

5.3 VISION BASED DEFECT DETECTION AND QUALITY INSPECTION

Timely detection of surface defects (weld cracks, corrosion, coating peeling) in metal components is crucial for structural safety. Traditional manual visual inspection is limited by subjective experience and working conditions, making it difficult to achieve large-scale, standardized quality control.

Convolutional neural networks (CNNs) have shown excellent performance in metal surface defect detection. The crack detection method based on deep learning proposed by Cha et al. achieved a detection accuracy of over 95% on both concrete and steel surfaces [48]. For weld quality assessment, researchers have developed specialized datasets and network architectures that can automatically identify typical defect types such as porosity, slag inclusions, and lack of fusion.

Three-dimensional point clouds can also be used for defect analysis. By comparing the deviation between the design model and the measured point cloud, the degree of geometric deformation of the component can be quantified. The M3C2 algorithm can directly calculate the signed distance between two-point clouds and identify surface anomalies such as local depressions or bulges [43]. This noncontact detection method is particularly suitable for steel structure inspection in high-altitude or hazardous areas.

By associating the visual inspection results with the BIM model, a component-level quality archive can be constructed. Each IfcElement instance is appended with attributes such as detection time, defect location, and severity, providing data support for maintenance decisions throughout the entire lifecycle.

6 CRITICAL TECHNICAL CHALLENGES AND FUTURE TRENDS

6.1 Heterogeneity between Geometric and Semantic Data

The primary challenge facing the integration of BIM and AI is data heterogeneity. BIM models are stored in a structured IFC format, emphasizing semantic integrity; while the point cloud, image, and other data processed by AI algorithms are essentially unstructured geometric information. There is a significant "semantic gap" between the two—models reconstructed from discrete point clouds are often just "dead geometry," lacking engineering semantics such as material properties and connectivity [49].

Bridging this gap requires the development of end-to-end semantic reconstruction methods. Future research should explore unifying semantic label prediction and geometric reconstruction into a single network framework to achieve direct mapping from raw scan data to semantically rich BIM models.

6.2 Scarcity of High-Quality Annotated 3D Datasets

The performance of deep learning is highly dependent on the scale and quality of the training data. However, the field of metal structures lacks large-scale labeled datasets similar to ImageNet or S3DIS. Labeling 3D point clouds requires specialized knowledge and is extremely time-consuming, which severely restricts the generalization ability of the algorithm.

Coping strategies include: (1) using BIM models to generate synthetic point clouds for data augmentation [34]; (2) developing weakly supervised and self-supervised learning methods to reduce the dependence on manual labeling; and (3) establishing open datasets shared by the industry to promote the comparable evaluation of algorithms.

6.3 Development of Neuro-symbolic AI in Engineering

The current mainstream deep learning models are essentially "black boxes," lacking interpretability and failing to meet the stringent requirements for safety and traceability in the engineering field. Neuro-symbolic AI combines the perceptual ability of neural networks with the logical rigor of symbolic reasoning, and is a noteworthy development direction [50].

In the management of metal components, this means that AI can not only identify "this is an H-shaped steel beam," but also reason "its flange thickness does not meet the specification requirements" and provide modification suggestions. This method of integrating data-driven and knowledge-driven approaches is expected to improve the credibility of AI systems in engineering decision-making.

6.4 Collaboration between Cloud and Edge Computing

Large-scale point cloud processing and real-time visual inspection place extremely high demands on computing power. Pure cloud solutions face data transmission latency and bandwidth bottlenecks, while edge devices have limited computing resources. A cloud-edge collaborative architecture, through the rational allocation of tasks—with lightweight preprocessing and real-time inference performed at the edge, and model training and complex analysis handled in the cloud—promises to achieve a balance between performance and efficiency.

With the widespread adoption of 5G networks and the development of edge AI chips, real-time intelligent perception at construction sites will become possible, driving the evolution of metal component management from "post-event analysis" to "real-time decision-making."

7 CONCLUSION

This study provides a systematic review of BIM and AI technologies in the fields of automated modeling and full lifecycle management of metal components. At the theoretical level, the IFC 4.3 standard significantly enhances the semantic expressive power of metal structures, and BIM and AI form a symbiotic relationship of "data-driven algorithms and algorithm-enabled models." However, semantic degradation during format conversion remains a key bottleneck. At the forward design level, deep learning-driven topology optimization has increased computational speed by two orders of magnitude, and generative adversarial networks provide diverse design solutions for complex nodes. At the reverse reconstruction level, point cloud deep learning methods, represented by RandLA-Net and Point Transformer, have broken through efficiency bottlenecks. Combined with RANSAC geometric extraction technology, the cross-section recognition rate of steel structure Scan-to-BIM has exceeded 90%. At the intelligent management level, knowledge graphs support automatic compliance checks, digital twin frameworks connect the design-manufacturing-assembly data chain, and CNN-based visual inspection achieves an accuracy rate of over 95% in metal defect identification. Current technologies still face challenges such as geometric-semantic heterogeneity, scarcity of labeled data, and insufficient model interpretability. Future development should focus on end-to-end semantic reconstruction, weakly supervised learning, neural symbolic AI, and cloud-edge collaborative architecture. The deep integration of BIM and AI is driving the evolution of metal component engineering from "labor-intensive" to "data-driven" and from "discrete management" to "end-to-end connectivity"..

ACKNOWLEDGMENTS

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions.

FUNDING

Not applicable.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

PUBLISHER'S NOTE

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

AUTHOR CONTRIBUTIONS

Not applicable.

ABOUT THE AUTHORS

LI, Zhuoxuan

School of Civil Engineering, Suzhou University of Science and Technology, Suzhou 215009, China.

REFERENCES

[1] Oesterreich, T. D., & Teuteberg, F. (2016). Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. Computers in industry, 83, 121-139.

[2] Sacks, R., Girolami, M., & Brilakis, I. (2020). Building information modelling, artificial intelligence and construction tech. Developments in the Built Environment, 4, 100011.

[3] Laefer, D. F., & Truong-Hong, L. (2017). Toward automatic generation of 3D steel structures for building information modelling. Automation in Construction, 74, 66-77.

[4] Sacks, R., Eastman, C., Lee, G., & Teicholz, P. (2018). BIM handbook: A guide to building information modeling for owners, designers, engineers, contractors, and facility managers. John Wiley & Sons.

[5] Tang, P., Huber, D., Akinci, B., Lipman, R., & Lytle, A. (2010). Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. Automation in construction, 19(7), 829-843.

[6] Volk, R., Stengel, J., & Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings—Literature review and future needs. Automation in construction, 38, 109-127.

[7] Wang, Q., & Kim, M. K. (2019). Applications of 3D point cloud data in the construction industry: A fifteen-year review from 2004 to 2018. Advanced engineering informatics, 39, 306-319.

[8] Pauwels, P., Zhang, S., & Lee, Y. C. (2017). Semantic web technologies in AEC industry: A literature overview. Automation in construction, 73, 145-165.

[9] Czerniawski, T., & Leite, F. (2020). Automated digital modeling of existing buildings: A review of visual object recognition methods. Automation in Construction, 113, 103131.

[10] Pătrăucean, V., Armeni, I., Nahangi, M., Yeung, J., Brilakis, I., & Haas, C. (2015). State of research in automatic as-built modelling. Advanced Engineering Informatics, 29(2), 162-171.

[11] Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. Automation in

Construction, 122, 103517.

[12] Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic Construction Digital Twin: Directions for future research. Automation in construction, 114, 103179.

[13] ISO. (2024). ISO 16739-1:2024 Industry Foundation Classes (IFC) for data sharing in the construction and facility management industries — Part 1: Data schema. International Organization for Standardization.

[14] Lipman, R. R. (2009). Details of the mappings between the CIS/2 and IFC product data models for structural steel. J. Inf. Technol. Constr., 14(1), 1-13.

[15] Venugopal, M., Eastman, C. M., Sacks, R., & Teizer, J. (2012). Semantics of model views for information exchanges using the industry foundation class schema. Advanced engineering informatics, 26(2), 411-428.

[16] Akinosho, T. D., Oyedele, L. O., Bilal, M., Ajayi, A. O., Delgado, M. D., Akinade, O. O., & Ahmed, A. A. (2020). Deep learning in the construction industry: A review of present status and future innovations. Journal of Building Engineering, 32, 101827.

[17] Zhu, A., Dai, T., Xu, G., Pauwels, P., De Vries, B., & Fang, M. (2023). Deep reinforcement learning for real-time assembly planning in robot-based prefabricated construction. IEEE Transactions on Automation Science and Engineering, 20(3), 1515-1526.

[18] Zhang, J., & El-Gohary, N. M. (2016). Semantic NLP-based information extraction from construction regulatory documents for automated compliance checking. Journal of computing in civil engineering, 30(2), 04015014.

[19] Wortmann, T., & Tunçer, B. (2017). Differentiating parametric design: Digital workflows in contemporary architecture and construction. Design Studies, 52, 173-197.

[20] Holzer, D. (2015). BIM and parametric design in academia and practice: the changing context of knowledge acquisition and application in the digital age. International journal of architectural computing, 13(1), 65-82.

[21] Eastman, C., Lee, J. M., Jeong, Y. S., & Lee, J. K. (2009). Automatic rule-based checking of building designs. Automation in construction, 18(8), 1011-1033.

[22] Davis, D. (2013). Modelled on software engineering: Flexible parametric models in the practice of architecture (Doctoral dissertation, RMIT University).

[23] Sosnovik, I., & Oseledets, I. (2019). Neural networks for topology optimization. Russian Journal of Numerical Analysis and Mathematical Modelling, 34(4), 215-223.

[24] Xiang, C., Wang, D., Pan, Y., Chen, A., Zhou, X., & Zhang, Y. (2022). Accelerated topology optimization design of 3D structures based on deep learning. Structural and Multidisciplinary Optimization, 65(3), 99.

[25] Yu, Y., Hur, T., Jung, J., & Jang, I. G. (2019). Deep learning for determining a near-optimal topological design without any iteration. Structural and Multidisciplinary Optimization, 59(3), 787-799.

[26] Oh, S., Jung, Y., Kim, S., Lee, I., & Kang, N. (2019). Deep generative design: integration of topology optimization and generative models. Journal of Mechanical Design, 141(11), 111405.

[27] Wu, C., Yuan, Y., Tang, Y., & Tian, B. (2021). Application of terrestrial laser scanning (TLS) in the architecture, engineering and construction (AEC) industry. Sensors, 22(1), 265.

[28] Besl, P. J., & McKay, N. D. (1992, April). Method for registration of 3-D shapes. In Sensor fusion IV: control paradigms and data structures (Vol. 1611, pp. 586-606). Spie.

[29] Qi, C. R., Su, H., Mo, K., & Guibas, L. J. (2017). Pointnet: Deep learning on point sets for 3d classification and segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 652-660).

[30] Qi, C. R., Yi, L., Su, H., & Guibas, L. J. (2017). Pointnet++: Deep hierarchical feature learning on point sets in a metric space. Advances in neural information processing systems, 30.

[31] Hu, Q., Yang, B., Xie, L., Rosa, S., Guo, Y., Wang, Z., ... & Markham, A. (2020). Randla-net: Efficient semantic segmentation of large-scale point clouds. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 11108-11117).

[32] Zhao, H., Jiang, L., Jia, J., Torr, P. H., & Koltun, V. (2021). Point transformer. In Proceedings of the IEEE/CVF international conference on computer vision (pp. 16259-16268).

[33] Daif, H., & Marzouk, M. (2025). Point cloud classification and part segmentation of steel structure elements. Neural Computing and Applications, 37(6), 4387-4407.

[34] Ma, J. W., Czerniawski, T., & Leite, F. (2020). Semantic segmentation of point clouds of building interiors with deep learning: Augmenting training datasets with synthetic BIM-based point clouds. Automation in construction, 113, 103144.

[35] Fischler, M. A., & Bolles, R. C. (1981). Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM, 24(6), 381-395.

[36] Yang, L., Cheng, J. C., & Wang, Q. (2020). Semi-automated generation of parametric BIM for steel structures based on terrestrial laser scanning data.

Automation in Construction, 112, 103037.

[37] Zbirovský, S., & Nežerka, V. (2025). Cloud2BIM: An open-source automatic pipeline for efficient conversion of large-scale point clouds into IFC format. arXiv preprint arXiv:2503.11498.

[38] Cheng, G., Liu, J., Li, D., & Chen, Y. F. (2023). Semi-Automated BIM Reconstruction of Full-Scale Space Frames with Spherical and Cylindrical Components Based on Terrestrial Laser Scanning. Remote Sensing, 15(11), 2806.

[39] Liu, J., Cui, N., Cheng, G., Li, D., Ma, X., & Liao, Y. (2023). Towards the automated virtual trial assembly of large and complex steel members using terrestrial laser scanning and BIM. Engineering Structures, 291, 116448.

[40] Lague, D., Brodu, N., & Leroux, J. (2013). Accurate 3D comparison of complex topography with terrestrial laser scanner: Application to the Rangitikei canyon (NZ). ISPRS journal of photogrammetry and remote sensing, 82, 10-26.

[41] Cha, Y. J., Choi, W., & Büyüköztürk, O. (2017). Deep learning - based crack damage detection using convolutional neural networks. Computer - Aided Civil and Infrastructure Engineering, 32(5), 361-378.

[42] Garcez, A. D. A., & Lamb, L. C. (2023). Neurosymbolic ai: The 3 rd wave. Artificial Intelligence Review, 56(11), 12387-12406.