



EG-ICE 2025 GLASGOW

LOAA: Towards a common understanding of the Levels of AI Automation in BIM authoring

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ABSTRACT:

This paper introduces a taxonomy for Levels of AI Automation (LOAA) that systematically classifies the involvement and autonomy of AI in BIM authoring. The taxonomy distinguishes two key phases within BIM authoring and proposes five levels of automation ranging from human-driven processes to complete AI autonomy. The taxonomy is grounded in established automation frameworks and CAD design evolution, and its applicability is demonstrated through case studies in BIM generative design and Scan-to-BIM scenarios. By categorizing recent publications into distinct LOAA levels, the proposed framework aims to guide researchers and practitioners in advancing AI integration in BIM authoring.

KEYWORDS:

Levels of Automation, Building Information Modeling, Artificial Intelligence

1. INTRODUCTION

Over recent decades, various attempts have been made to digitize processes around the planning, construction, and operation of assets in the built environment. The notion of Building Information Modeling (BIM) describes a comprehensive method to produce, communicate, and analyze digital building models (Eastman et al., 2008), enabling geometric and semantic information to be utilized throughout the building's life cycle (Borrmann et al., 2018). However, creating BIM models is often perceived as a cumbersome, complex, and manual task (Du, Deng, et al., 2024). The emergence of applicable Artificial Intelligence (AI) methods exhibits its potential to play a crucial role in automating the BIM authoring of building assets from various data sources (e.g., point clouds, textual requirements, architectural sketches, etc.), enabling efficient processing and reducing the risk of manual errors. As AI increasingly influences BIM authoring, understanding the different levels at which this technology is being applied is becoming important to enable practitioners and researchers to engage with current studies, methodologies, and industry approaches.

Existing review papers typically discuss the contributions of current research to automation in the AEC (Architecture, Engineering, Construction) field from the perspective of specific disciplines (C. Li et al., 2024; Liao et al., 2024), technologies and algorithms (Kookalani et al., 2024), or application cases (Rashdi et al., 2022; Sacks et al., 2020). However, there is a lack of a dedicated taxonomy to systematically organize and define Levels of AI Automation in BIM authoring, which we refer to as **LOAA**.

Levels of Automation (LOA) frameworks have long been used in other fields (e.g., manufacturing, vehicles) to describe how tasks are allocated between humans and machines. This paper reviews prominent LOA frameworks in these fields, drawing from established automation theories and analyzing the evolution of CAD design automation. A new LOAA taxonomy tailored for BIM authoring is proposed, as illustrated in Figure 1. The taxonomy's applicability is demonstrated by classifying several recent publications on AI applications in BIM authoring according to the proposed LOAA levels. By providing such a classification system, this paper aims to provide a categorization to help researchers and

industry professionals better understand the current status and future trajectory of AI automation in BIM authoring.

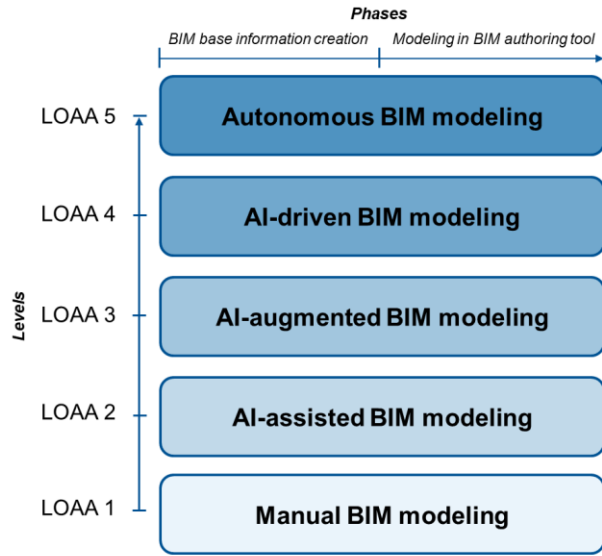


Figure 1: Five Levels of AI Automation (LOAA) in BIM authoring

2. DEFINITION, SCOPE AND RESEARCH QUESTIONS

The purpose of this paper is to introduce the concept of LOAA to the context of BIM authoring. Referring to (Borkowski, 2023), we define the **BIM model** as the object-oriented data representation that includes the 3D geometry of building objects and semantic data such as object types, properties, and relationships, as well as the parametrization of objects. From this, we define **BIM authoring** in this paper as *the process of generating the BIM model using BIM authoring tools (based on necessary intermediate representations)*.

The raw inputs or data sources required for BIM authoring can include building regulations, client requirements, survey point clouds of existing buildings, image documentation, sketches or texts that reflect the architectural creativity, etc. These inputs can come from application scenarios involving retrofitting existing buildings or designing new ones.

Based on the above definition, BIM authoring activities are divided into two main phases:

- **BIM base information creation:** This involves extracting or synthesizing the necessary information for producing a BIM model or guiding its creation from raw and noisy, potentially multi-modal data sources as mentioned before. This phase does not involve the actual creation of the BIM model itself.
- **Modeling in BIM authoring tools:** This refers to the process of creating and interacting with the BIM model (e.g., retrieving, updating, and

deleting objects) based on the information obtained in the previous phase.

The research questions explored in this study are as follows:

- **RQ1:** Are existing general LOA frameworks and design automation classifications sufficient for classifying AI automation within the BIM authoring process?
- **RQ2:** What are appropriate dimensions and levels for a new LOA taxonomy that captures the varying degrees of AI automation across both phases? How do concepts from existing CAD automation (rigid, parametric, feature-based, knowledge-based, generative design) relate to our taxonomy?
- **RQ3:** Can the proposed taxonomy be effectively applied to classify the existing research on BIM authoring automation?

3. BACKGROUND AND RELATED WORK

3.1 Existing LOA Frameworks

The concept of Levels of Automation (LOA) is widely discussed across disciplines such as manufacturing, robotics, automotive, and design (Altavilla & Blanco, 2020). LOA can be broadly defined as a measure of the extent to which functions, activities, or tasks are automated, ranging from fully manual control to complete automation (Billings, 1997). Lindström et al. (2008) explore the definition of LOAs in manufacturing, which is used to classify how tasks are distributed between human workers and automated systems. In this, the authors present LOA as a continuum, where at one end, tasks are manually performed by humans, while at the other end, they are fully automated, requiring minimal or no human intervention. (Lindström et al., 2008)

In the automotive field, many industry organizations propose using LOA to describe the degree or category of a vehicle's autonomy. For example, the German Federal Highway Research Institute (BAST) defines five levels, ranging from "driver-only" to "fully automated" (Gasser & Westhoff, 2012). Here, LOA is used to classify the transfer of driving tasks and environmental perception from human drivers to automated systems and technologies. This approach portrays vehicle automation as a series of technologies and capabilities, helping to break down the process of achieving vehicle automation into distinct steps or stages (Hopkins & Schwanen, 2021).

Parasuraman et al. (2000) develop a multi-dimensional LOA model. Their framework identifies four basic functions within human-machine systems that can be automated: information acquisition, information analysis, decision and action selection, and action implementation (Parasuraman et al., 2000). A key innovation of this model is the recognition that automation is not a single concept; rather,

different stages of information processing in a task can have varying degrees of automation. Across these four functional categories, automation levels can range from low (tasks performed manually by humans) to high or fully automated (tasks executed independently by computers). For instance, a system might exhibit high automation in information acquisition but low automation in decision and action selection. This differentiation is insightful for understanding how AI can integrate into BIM authoring processes, as various AI applications may target specific phases of BIM authoring (as defined in Section 2) and automate these phases to varying degrees.

In general design contexts, Altavilla & Blanco (2020) define five levels to measure the interaction between human designers and AI tools, ranging from full human control (Level 1) to complete AI automation (Level 5). Using the GEMS cognitive model (Srinivasan & Chakrabarti, 2010), Altavilla & Blanco classify the design process into four types of activities:

- **Generate:** Creating ideas or solutions based on requirements.
- **Evaluate:** Assessing the quality or feasibility of the generated ideas.
- **Modify:** Make changes to improve or adjust the design.
- **Select:** Choosing the best option from a set of alternatives.

A LOA taxonomy is then applied to evaluate how these four activities are distributed between humans and AI tools and characterize the degree of automation in the design process. (Altavilla & Blanco, 2020)

In the field of architecture, Rafizadeh et al. (2024) categorize architectural activities into *Creative and Documentation Tasks* and *Fabrication and Construction Tasks*, proposing separate LOA models for each. For example, for *Creative and Documentation Tasks*, they defined five automation levels: manual drawing, digitization (using BIM or CAD software tools), parametric design, computational & generative design (simulation and optimization), and generative AI (Rafizadeh et al., 2024). While their LOA model adopts a broader scope and emphasizes traditional rule-based design automation approaches, our taxonomy focuses specifically on discussing AI-driven automation of BIM authoring processes at a more granular level.

3.2 Evolution of CAD Automation

To analyze the impact of AI automation on BIM authoring, it is essential to understand the historical progression of automation within the field of Computer-Aided Design (CAD). CAD automation has

evolved through several phases, each building upon the previous stages.

Rigid Modeling. Early CAD systems mainly allow users to create basic geometric shapes (lines, arcs, circles) without intelligence or adaptability. Modifications to these models often require manual redrawing or adjustments.

Parametric Design. This method introduces parameters to define geometric shapes. The core idea is that geometry is governed by parameters (such as dimensions, distances, etc.) and constraints (mathematical relationships): When parameter values change, the model automatically updates to reflect these changes while complying with the constraints (Borrmann & Berkhahn, 2018; H. Li et al., 2020). Parameters typically require manual definition; designers can alter designs simply by adjusting parameter values.

Feature-Based Design. Feature-based modeling extends parametric design, allowing designers to create models from engineering features. These features encompass not only geometric information but also design intent and manufacturing considerations (Başak & Gülesin, 2004). Features represent common engineering shapes or manufacturing operations (e.g., extrusion, revolution, holes, fillets, chamfers, shells) (Fan et al., 2025). By organizing designs around these features, designers can focus on higher-level design concepts rather than low-level geometric entities. Each feature is defined by adjustable parameters, allowing designers to modify models by changing parameter values. This approach relates to object-oriented concepts (Zhou, 2023) within BIM modeling.

Knowledge-Based Design. The core idea of knowledge-based design is the integration of engineering knowledge such as rules, best practices, standards, and logic directly into CAD systems (Häußler & Borrmann, 2021; Jubierre & Borrmann, 2015). It aims to automate repetitive, rule-driven design tasks based on captured expert knowledge. These expert systems typically use parametric and feature-based models as their foundation and can autonomously apply design rules to complete complex designs. A critical challenge lies in effectively capturing and translating expert knowledge into complex formulas and conditional logic (if-then statements) (Kreis et al., 2020).

Generative Design. Generative design utilizes algorithms (e.g., optimization algorithms) to automatically generate multiple design alternatives based on user-defined constraints and objectives (Chew et al., 2024). Designers specify parameters like material properties, performance goals, cost limitations, etc., and the system explores a broad solution space to produce numerous viable design options.

Table 1 Levels of AI Automation (LOAA) in BIM authoring

	LOAA	Phase 1: BIM Base Information Creation	Phase 2: Modeling in BIM Authoring Tool	Overall Description
1	Manual BIM Authoring	Human analyzes inputs	Human creates all elements and inputs data in the tool.	Entire process is human-controlled and executed without AI involvement.
2	AI-Assisted BIM Authoring	AI provides basic information analysis. Human directs and validates.	AI offers suggestions or automates minor tasks. Human performs most modeling.	AI as assistant, providing information and minor task automation; Human leads.
3	AI-Augmented BIM Authoring	AI performs more complex analysis. Human reviews and corrects.	AI automates specific modeling sub-tasks or generates partial model elements. Human integrates and models complex parts.	AI takes over defined sub-tasks in both phases, augmenting human capabilities.
4	AI-Driven BIM Authoring	AI largely automates information interpretation and structuring. Human approves or overrides.	AI autonomously generates significant portions of the model. Human focuses on validation and exceptions.	AI drives the generation of both information and model components; Human oversees and refines.
5	Autonomous BIM Authoring	AI fully automates analysis and information interpretation. No/minor human intervention.	AI fully automates model creation, assembly, and metadata input. No/minor human intervention.	AI autonomously handles the entire process.

The evolution of CAD automation clearly demonstrates a trend towards increasing intelligence and automation within design tools. The LOA explored in this study regarding BIM authoring focuses on the future steps of this evolution, i.e., the impact of AI on modern BIM authoring tools built on these automated methods. In addition, the mentioned CAD automation stages largely rely on or assume manually extracted and defined logic or rules, mainly emphasizing CAD modeling operations in design tools. While the AI automation in BIM authoring tools is built upon these methods, the classification proposed in this paper extends the scope by also exploring the potential of AI to automate information engineering steps required for BIM authoring, which we refer to as BIM base information creation.

4. THE LEVELS OF AI AUTOMATION IN BIM AUTHORIZING

The multidimensional LOA framework in (Parasuraman et al., 2000) provides a valuable basis for analyzing AI automation in BIM authoring. However, the unique characteristics of the BIM authoring process require careful consideration of how general LOA aligns with specific domain details. BIM is essentially an object-oriented approach that goes beyond simple geometric representations, encompassing rich geometric, semantic, and topological information. Therefore, as defined in Section 2, we abstract the BIM authoring process into two consecutive phases.

Phase 1: BIM base information creation resembles the "Information Analysis" described by (Parasuraman et al., 2000). Examples include analyzing as-built conditions captured by laser scans using Computer Vision (CV), identifying building elements

from floor plans using Graph Neural Network (GNN), or parsing design requirements or regulations through Natural Language Processing (NLP). The focus here is on the degree to which the AI system understands design contexts before performing actual modeling (authoring) operations.

Phase 2: Modeling in BIM authoring tool based on the information captured in the previous phase, including creating and authoring BIM elements, assembling them into a coherent model, and inputting relevant metadata. It reflects the extent to which the system employs AI during actual authoring operations within design software.

Given this two-phase structure, an effective classification must consider how automation is applied in each phase, to what extent, and the phase integration. Existing LOA models typically assume a simple continuum from human to machine control. However, in BIM authoring, AI may automate phase 1 (e.g., automatically segmenting building elements from scanned point clouds) while leaving phase 2 manual (where the user inserts objects in BIM authoring tools based on segmentation results). Conversely, another scenario might involve human users providing machine-readable design information in phase 1, with AI automating phase 2.

Considering these aspects, we propose a five-level Levels of AI Automation (LOAA) classification. Each level is defined by the degree of AI automation and human involvement across phase 1 and 2, illustrated in Table 1.

The manual BIM authoring at **LOAA 1** represents a traditional workflow entirely dependent on human cognition and operations within BIM software. At this level, there is no AI involvement; however, existing rule-driven automation in the design software, as

described in Section 3.2, still exists. In phase 1, human users manually interpret or write scripts to interpret all inputs, such as reading drawings and understanding textual requirements, synthesizing this information primarily through mental models. Subsequently, in phase 2, conventional workflows (including rule-driven automation) are executed within the software. The information transferred between phases remains human-centric and does not require specific formats suitable for AI systems, as no AI processing occurs at phase 2.

In **LOAA 2**, AI acts as an assistant to enhance user efficiency. In phase 1, AI assists with basic analysis to generate machine-readable representations, such as simple structured data formats (e.g., lists of identified elements, coordinates, object properties, user interaction history, etc.). In phase 2, the AI parses this information to provide context-specific aids within BIM authoring tools (e.g., suggesting parameters or placements, recommending next commands, or leveraging existing rule-based CAD automation methods to automate minor tasks, etc.). However, the primary information flow and decision-making remain in human control.

In **LOAA 3**, AI undertakes specific, well-defined, and more complex tasks, thereby enhancing human capabilities across two phases. To enable AI in phase 2 to automatically perform relevant modeling subtasks, the information representations extracted by AI in phase 1 must be more detailed. As humans remain integrated within the modeling process, the BIM base information created by AI does not necessarily need to fully capture all geometrical, semantic, and topological information. Another key distinction from LOAA 2 is that when AI automates specific modeling sub-tasks or generates partial model elements, it must make its own decisions rather than relying primarily on predefined human rules and logic.

The transition to **LOAA 4** marks a significant shift, with AI dominating the interpretation of raw data and model generation, while humans move towards a supervisory role. At this level, the boundary between phases 1 and 2 begins to blur, as a unified AI system may emerge capable of autonomously generating significant portions of BIM models end-to-end from raw data. This requires AI to encode extensive multimodal raw data into informative intermediate representations (e.g., detailed graphs, domain-specific languages, or high-dimensional latent representations encoding complex patterns or design intents) in phase 1, and subsequently decode these representations in phase 2 to produce BIM models. BIM authoring software needs to evolve from being primarily a tool for direct human manipulation into an execution platform for AI-driven processes. This requires capabilities such as native AI integration,

comprehensive APIs allowing AI systems to programmatically drive model creation, software interfaces adapted for human oversight, and software architectures capable of decoding latent representations or running generative algorithms, etc.

LOAA 5 represents the highest level of AI automation, where an end-to-end AI system autonomously manages the entire process from initial inputs to a fully completed BIM model with minor or no human intervention. Phases 1 and 2 may be internalized within the AI system itself. AI at this level must fully automate the acquisition, analysis, synthesis, and construction of all necessary BIM base information from various data sources as mentioned in Section 2 (e.g., building regulations, client requirements, architectural creativity, or scanned point clouds of existing buildings, etc.). Such information must encode not only geometric, topological, and semantic data, but also complex constraints, high-level objectives, cross-disciplinary dependencies, etc., enabling the AI to autonomously generate, coordinate, and finally validate a complete BIM model. The BIM authoring software is essentially replaced by the AI system.

5. CASE STUDIES

In this section, the proposed LOAA taxonomy is applied to recent publications focusing on two representative BIM authoring scenarios, i.e., BIM generative design and Scan-to-BIM, which respectively exemplify forward and reverse modeling use cases. The goal is to analyze the contributions of recent publications from the perspective of AI automation, locate the current research status, and outline future developments.

5.1 BIM Generative Design

Ma et al. (2021) break down generative design within BIM into two key parts: design constraints and algorithms. Design constraints are conditions or preferences defined in a computer-readable format, such as spatial/form requirements, dimensional constraints, material choices, and cost limits. Algorithms optimize and search the model parameters to generate various design options.

Cuellar Lobo et al. (2021) present a BIM-based generative design framework aimed at optimizing drywall installation planning in prefabricated construction. They develop scripts to pull geometric, material, and cost information from BIM models, converting these into XML format. Given this machine-readable data, a heuristic optimization algorithm is employed to minimize material waste, while a fuzzy analytical hierarchy process (AHP) ranks the alternatives based on environmental impact, cost, and aesthetic criteria. Finally, Dynamo scripts are employed to generate the BIM model from

parameters. Although the proposed framework automates drywall design, it relies on manually hard-coded scripts and optimization algorithms with predefined objective functions to extract BIM base information and create models, rather than using AI to learn from data. Therefore, this study can be classified as LOAA 1.

Similarly, Gan (2022) proposes a method to automate the design of modular buildings. Various information is collected in IFC Model View Definition (MVD) and formulated as graph-structured data containing necessary BIM base information. Dynamo is used to interpret information to generate a BIM model. Since the entire method is still based on traditional automation tools, it is also classified as LOAA 1. The same classification applies to another generative design approach for the use case of integral residential energy-efficient façades (Ma & Wang, 2025).

K. Li et al. (2024) propose a method for the automated generative design of precast buildings. They introduce a graph-based representation to abstract the spatial and geometric parameters of BIM models. A system that interfaces with BIM authoring tools is implemented, which leverages optimization algorithms to explore the parameter space, generating various design options. A graph neural network is employed to classify whether the graph of each generated model corresponds to an optimal layout. In this study, the BIM base information creation phase (i.e., graph representation) involved no AI intervention and is therefore categorized as LOAA 1. However, during the model creation phase, the graph neural network is used to automate model evaluation, which qualifies this stage as LOAA 2.

The modeling scenarios discussed in this section can also be extended to a more general BIM authoring process. Du et al. (2024) preprocess BIM log data to extract effective command sequences and use them to train a Transformer model that suggests the next best commands during the BIM authoring process. In this study, information creation in phase 1 is human-driven, achieving LOAA 1. Although modeling remained manual in phase 2, the AI provides suggestions, thus reaching LOAA 2.

The LLM-based copilot (Du, Nousias, et al., 2024; Fernandes et al., 2024) in the BIM authoring tool can invoke and combine predefined tool functions based on natural language instruction to automate information retrieval and assist modeling. Although some contextual knowledge must be hardcoded into the prompt templates, LLM still decides which tools to employ and converts the prompt into the machine-readable inputs required to invoke the corresponding tools. Therefore, this research can be classified as LOAA 2. Text2BIM framework (Du, Esser, et al., 2024) further coordinates multiple LLM agents to

generate code for BIM models. Similar to previous studies, it employs prompt engineering in phase 1 to achieve LOAA 2. However, in phase 2 it can reach LOAA 3 because, while writing code, the LLM must make its own decisions rather than relying primarily on predefined human rules to produce early-stage architectural models.

5.2 Scan-to-BIM

The primary focus of Scan-to-BIM research is to automate the process of generating BIM models from point clouds, thereby enabling the digitization of existing buildings (Noichl et al., 2024).

In the study by (Mehranfar, Vega-Torres, et al., 2024), the PointTransformer model is used to semantically segment point clouds. Spaces are detected based on these segmentation results and a neighborhood graph structure. Planes, doors, and windows are fitted using RANSAC etc., before using the Revit API to create a BIM model. This approach leverages AI to extract BIM base information from point clouds, reaching LOAA 2, whereas the modeling process in Revit still relies on hard-coded scripts, thus remaining at LOAA 1. Other similar studies (Mahmoud et al., 2024; Mehranfar, Braun, et al., 2024) follow the same classification scheme.

Song et al. (2023) propose an assistive system that helps Scan-to-BIM by predicting the next modeling operations. Rather than reconstructing fully automatically, this method provides interactive suggestions in BIM authoring tool that designers can accept or modify. Specifically, it first employs a Transformer-based corner-detection module to identify corners and enumerate candidate walls in point clouds. Another Transformer network is then used to predict the placement of the next wall from the candidate walls and authoring history, thereby achieving LOAA 2.

5.3 Summary and Outlook

Recent publications in BIM authoring reveal that while traditional automation methods remain predominant, the integration of AI is steadily advancing across both generative design and Scan-to-BIM research. In the field of generative design, early work largely relied on hard-coded scripts and optimization algorithms (LOAA 1). AI is increasingly being used for intermediate tasks such as suggestion generation (LOAA 2). Notably, LLM-based agentic systems are beginning to move decision-making away from human-defined rules toward more autonomous processes, at times reaching LOAA 3.

In Scan-to-BIM workflows, AI has proven effective at processing raw point clouds and enriching it with semantic information. However, integration with BIM authoring tools still depends on manually defined scripts during the modeling process, limiting

overall automation to LOAA 1 or 2. There is a lack of structure in the results of semantic enrichment processes. With a structured handover of these results, approaches in the domain of Scan-to-BIM will reach LOAA 3 modeling as subsequent processing steps can be adopted from BIM generative design methodologies.

Overall, future research is expected to focus on reducing reliance on predefined rules and hard-coded scripts. The goal is to create end-to-end automated AI systems that provide holistic solutions for all related use cases.

A potential limitation of our current taxonomy is the omission of explicit consideration for the level of information accessed or generated by the AI, which may introduce some ambiguity in classification. Future work could address this by integrating the Levels of Development (LOD), allowing a more nuanced classification based on both autonomy and the depth of information processing.

6. CONCLUSION

This paper introduced the Levels of AI Automation in BIM Authoring (LOAA) taxonomy that bridges the gap between general LOA frameworks and the specific needs of BIM authoring processes. By dividing the overall process into two phases, i.e., BIM base information creation and modeling within BIM authoring tools, the proposed five-level taxonomy offers a structured approach to evaluate and compare AI integration in the AEC industry.

Our analysis of recent publications in BIM generative design and Scan-to-BIM scenarios demonstrates that while many existing methods fall within LOAA 1 and LOAA 2, emerging studies are beginning to leverage AI for more complex sub-tasks (LOAA 3), indicating a shift towards increased AI automation.

The development of end-to-end AI systems is expected to become a research frontier, capable of autonomously managing information extraction and model creation (targeting LOAA 4 and LOAA 5). Future work should continue to focus on reducing human intervention, enhancing multimodal data processing, and re-thinking BIM authoring tools and workflows to be AI-native.

ACKNOWLEDGEMENT

This work is funded by Nemetschek Group, which is gratefully acknowledged.

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