Automating Electrical Outlet and Circuit Assignment in BIM through AI-Assisted CAD–BIM Interoperability

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Abstract – Electrical system modeling in BIM environments still relies heavily on manual interpretation of 2D CAD drawings, which can propagate circuit and panelboard assignment errors and increase rework. This paper presents an AI-driven, a parametric CAD–BIM workflow that automates outlet-to-circuit assignment and circuit-to-panelboard connections while maintaining semantic traceability. CAD plan views are captured as images and processed with a multimodal large-language model (Microsoft Copilot). Through iterative prompt engineering, the system extracts outlet identifiers, associated distribution board, and element counts, and exports a structured Excel dataset for downstream automation. Autodesk Dynamo and Python then ingest the dataset, match it to Revit parametric families, and execute rule-based logic to generate circuits and connect them to the target panelboard. The approach was validated on five real case studies from a data-center project by comparing a conventional manual Revit procedure against the automated workflow using execution time and review-stage errors as performance metrics. For 42 outlets, the manual procedure took 31.5 minutes and produced six misassignments, whereas the automated routine completed in 0.033 seconds with zero errors; for 24 outlets, the manual procedure took 12 minutes with two errors, while the automated routine took 0.025 seconds with zero errors.

Keywords – Building Information Modeling (BIM); CAD–BIM Interoperability; Artificial Intelligence; Electrical System Automation; Parametric Modeling; Dynamo Scripting

1 Introduction

The increasing scale and technical complexity of contemporary construction projects have intensified the demand for accurate, consistent, and interoperable information management across the design and execution stages [1]. In this context, electrical system planning remains heavily dependent on two-dimensional CAD documentation, in which circuit layouts, outlet distributions, and panel assignments are commonly interpreted manually, introducing coordination risks and propagating errors into downstream BIM processes [2]. Although Building Information Modeling has enhanced multidisciplinary coordination and centralized data, its application to electrical design workflows is often constrained by fragmented information transfer between CAD drawings and BIM environments [3]. These limitations become particularly critical when repetitive components, standardized electrical conventions, and regulatory requirements must be maintained consistently across multiple project iterations [4]. Deficiencies in early-stage electrical data integration can lead to misaligned circuit assignments, inconsistent schedules, and increased rework during construction, directly affecting project cost, time, and model reliability. Current digital practices, including spreadsheet-based coordination and rule-based verification, provide partial support but continue to rely heavily on manual intervention. As a result, recent research has increasingly explored artificial intelligence and parametric programming as enabling technologies for interpreting structured graphical information and implementing automated logic within BIM workflows [5]. By combining AI-assisted extraction of graphical inputs with parametric scripts that support semantic matching and rule-driven classification, it becomes feasible to bridge the persistent gap between CAD-based electrical plans and BIM models [6]. This integration supports automated outlet identification, circuit correspondence, and panel allocation while preserving consistency between design documentation and digital representations. In this setting, the convergence of CAD inputs, AI-driven data structuring, and parametric automation within BIM platforms emerges as a promising pathway to enhance reliability, reduce human error, and improve efficiency in electrical system modeling [7].

The accelerated adoption of artificial intelligence across industrial domains has reshaped how technical information is processed, interpreted, and operationalized, particularly in environments with large volumes of graphical data and repetitive decision rules [8]. In construction-related workflows, AI-driven solutions have progressively enabled automated drawing interpretation, data structuring, and rule-based decision support, offering new opportunities to reduce manual effort and improve consistency in digital models [9]. Within BIM-centered processes, these technologies have been applied to scheduling, coordination, and analytical tasks, providing near-real-time feedback that was previously unattainable with conventional tools. At the same time, advances in machine learning and generative systems have enabled the transformation of unstructured visual inputs into structured datasets that parametric environments can directly consume. This capability is especially relevant in electrical design processes, where information embedded in CAD drawings must be accurately translated into BIM elements while preserving naming conventions, circuit logic, and panel relationships. Despite these advances, adoption remains uneven due to organizational inertia, limited standardization, and the technical complexity of integrating AI outputs into interoperable BIM workflows [10]. Lightweight, task-oriented AI tools have recently emerged as a practical entry point for embedding intelligence into traditional manual processes, enabling incremental experimentation with lower implementation barriers [11]. However, a clear methodological gap persists in integrating AI-based graphical extraction, intermediate data processing, and parametric automation into a coherent end-to-end workflow. Addressing this gap is essential to move from isolated AI applications toward reliable automation strategies that support data-driven decision-making and consistent model generation in BIM-based electrical system design [12].

Although prior research has extensively examined the application of artificial intelligence and automation within BIM-based environments, most contributions have focused on isolated tasks or domain-specific use cases, leaving unresolved questions about their systematic integration into end-to-end design workflows [6]. Existing studies have explored AI-driven methods for graphical information extraction [13], parametric modeling strategies, and interoperability solutions between CAD and BIM platforms [14], demonstrating measurable improvements in efficiency and data consistency. However, these approaches are often implemented independently, without a unified methodological structure that integrates graphical interpretation, intermediate data processing, and automated model generation within a single workflow. Limited attention has been paid to electrical design processes, in which circuit logic, outlet distribution, and panel assignment rely heavily on manual interpretation of CAD drawings and on repetitive decision rules. The lack of integrated solutions to automate these tasks contributes to inconsistencies between design documentation and BIM models, increasing coordination effort and the propagation of errors. In response to this gap, this research aims to propose an AI-driven, parametric workflow that systematically links CAD-based electrical drawings, automated graphical information extraction, structured data processing, and BIM model generation through programming-based automation. The proposed approach enables the automated identification and assignment of electrical outlets and circuits while preserving semantic coherence

parametric programming, and CAD–BIM interoperability within a unified framework, this study advances a reproducible, scalable methodology that addresses critical limitations identified in the current literature and supports more reliable digital modeling of electrical systems.

2 Literature Background

The growing complexity of construction projects and the increasing reliance on digital workflows have reinforced Building Information Modeling (BIM) as a central platform for managing geometric and semantic information throughout the project lifecycle [15,16]. Although BIM has demonstrated significant benefits in coordination and information integration, its effectiveness is often constrained by continued reliance on two-dimensional CAD-based documentation, which requires manual interpretation and limits automation potential [2]. Recent research has therefore shifted toward incorporating computational and data-driven approaches to enhance the transformation of graphical information into structured BIM environments [17]. Advances in artificial intelligence, parametric programming, and interoperability strategies have enabled new methods for extracting, processing, and reusing design data with reduced human intervention [18]. Studies indicate that integrating image-based analysis, rule-based logic, and visual programming can improve consistency, traceability, and scalability in BIM workflows, especially in disciplines characterized by repetitive elements and strict design conventions [19]. Despite these developments, the literature remains fragmented regarding how these approaches are jointly implemented within coherent methodological frameworks. This fragmentation highlights the need for a structured review of existing contributions addressing AI-based graphical information extraction, parametric automation in BIM, and CAD–BIM interoperability, as foundational components for advancing automated and reliable digital modeling processes.

Recent academic contributions reveal a growing focus on integrating artificial intelligence, parametric automation, and interoperability within BIM-based workflows, driven by the need to reduce manual modeling and improve semantic consistency across digital construction processes. Montas-Laracuente et al. [20] presented a systematic examination of AI-driven Scan-to-BIM strategies, highlighting the dominance of deep learning approaches for semantic segmentation of point clouds and images, while exposing limitations in end-to-end automation and BIM interoperability. Kutá et al. [21] offered a comprehensive overview of AI adoption throughout BIM-enabled project lifecycles, demonstrating advances in automation, generative processes, and digital twins. However, their analysis underscored the dependence on structured data and expert validation. Araya-Aliaga et al. [22] introduced an integrated AI–BIM framework to automate the generation and validation of geometric and semantic information, reporting higher model coherence, reduced manual effort, and improved data traceability. Harle [23] extracting visual and geometric data within BIM environments, reporting enhanced element recognition alongside unresolved challenges related to model generalization and platform interoperability. Taken together, these studies reflect steady progress in AI-assisted BIM workflows, yet they consistently point to fragmented implementations across disciplines and project stages.

Building on these developments, further research has advanced AI–BIM integration to support safety monitoring, parametric reconstruction, and performance-driven analysis. Wang et al. [24] demonstrated the feasibility of computer vision–based systems for identifying construction activities and unsafe behaviors from site imagery, achieving high accuracy in real-time safety monitoring. Salmi et al. [25] proposed a BIM-based parametric modeling strategy for generating Mine Information Models from heterogeneous spatial datasets, showing that algorithmic rules and parametric objects enable accurate reconstruction with limited human intervention. Semjén et al. [26] synthesized existing knowledge on parametric and generative design within BIM workflows, revealing optimization gains during early design phases while noting persistent issues related to standardization and lifecycle integration. Kamel et al. [3] analyzed BIM–BEM interoperability processes, identifying semantic inconsistencies and data loss during information exchange. Su et al. [27] developed a BIM–machine learning framework for automated property valuation that combines IFC data with optimized regression models, achieving higher accuracy than traditional methods. Zhang et al. [28] integrated BIM for building energy efficiency, highlighting its role in energy prediction and lifecycle assessment, but noted that interoperability issues and costs limit adoption. Collectively, the literature depicts a landscape in which AI, parametric automation, and interoperability are treated as partially isolated components. In response to this gap, the present paper advances an integrated methodology that connects CAD-based electrical drawings, AI-assisted graphical information extraction, and parametric automation in Dynamo to automate the assignment and connection of electrical outlets in BIM models. This contribution introduces a structured, end-to-end workflow that enhances consistency, reduces errors, and improves efficiency in electrical modeling processes, directly addressing limitations identified in prior studies.

3 Research Method

3.1 Image-Based Data Extraction Process

The methodological workflow began by formalizing a procedure for extracting information from CAD-derived images of electrical layouts, with a focus on outlet tags and distribution boards, as shown in plan views. A multimodal large language interface (Microsoft Copilot) was then utilized to identify and parse the visual attributes embedded in the CAD imagery. To ensure reliable extraction, a structured prompt engineering process was conducted through iterative refinement, ambiguity in label detection, color-based classification, and record structuring. After approximately 20 iterations, a stable prompt specification was established, enabling the automated identification of three key variables for downstream automation: the outlet identifier, the associated panelboard, and the count of outlets in the drawing segment.

The extracted information was exported into a structured Microsoft Excel file, which served as the standardized input dataset for the subsequent parametric assignment of outlets to panels and circuits within Autodesk Revit. Prompt calibration was conducted using three representative CAD images. Simultaneously, two professionals with extensive experience in interpreting CAD electrical drawings independently reviewed the same images and generated reference reports, which served as a baseline for comparison. The final prompt achieved complete agreement with the expert-derived outputs on the calibration set, confirming its reliability as a preprocessing mechanism for transforming unstructured plan-image content into machine-readable data for BIM-based automation. **Error! Reference source not found.** shows the instructions for generating the prompt for data extraction.

Table 1. Prompt used in data extraction.

Id	Actions	Instructions
1	Label identification	- Extract all visible labels in the image. - Each label follows the format BaseText-#Number. - Read and process the image from top to bottom. - If the first element is blue, classify it as Secondary (S) and the next as Primary (P), alternating thereafter. - If the first element is red, classify it as Primary (P) and the next as Secondary (S), alternating thereafter.
2	Base-text cleaning	- Remove the suffix -#Number and keep only the base text (e.g., RPPBB112-#1 → RPPBB112).
3	Table generation	- The table must contain three columns: a) Type: P or S b) Base label: the base text without the suffix c) Count: a consecutive index starting at 1 and ending at the total number of elements.

Although the prompt reached full agreement with the expert-generated outputs for the calibration images, the AI extraction stage should be interpreted as a calibrated preprocessing component rather than as a universally deterministic procedure. Because multimodal large language models may exhibit non-deterministic behavior, the reproducibility of the extraction depends on maintaining the same prompt structure, image preparation criteria, and review protocol. The extraction is also sensitive to variations in drawing legibility, annotation density, color conventions, and screenshot quality, which may affect robustness when different CAD standards are used. For this reason, the workflow incorporates expert validation during calibration and fixes the final prompt before evaluation. In addition, the present study assessed the extraction process only with Microsoft Copilot; therefore, the transferability of the results to other AI tools remains a relevant limitation that should be examined in future research.

3.2 Development of an Automated Tool in a BIM Environment

The BIM tool that automates the assignment of electrical outlets to distribution boards, leveraging the structured dataset produced by the Microsoft Copilot–based analysis, was implemented using Autodesk Dynamo as the primary development environment. As a prerequisite, a dedicated library of parametric families was created in Autodesk Revit to represent outlets and distribution board, encoding the key attributes required for identification, matching, and subsequent parameter assignment. These families were designed to conform to the labeling logic and graphical conventions observed in the CAD drawings analyzed by the AI component, thereby ensuring semantic alignment among the source documentation, the extracted Excel dataset, and the target BIM model. The Dynamo algorithm was structured into three main modules: (1) an input-processing module responsible for reading, parsing, and validating the Excel file generated by the AI pipeline; (2) a matching module that compares outlet identifiers obtained from the spreadsheet with the corresponding identifiers embedded in the Revit family instances, incorporating basic normalization rules to reduce mismatches due to formatting differences; and (3) an assignment module that programmatically links each matched outlet instance to its corresponding panelboard within the BIM model by writing the appropriate parameter values. In this third module, once a valid name-based correspondence is detected, the algorithm automatically populates the outlet instance with the associated board information, enabling consistent model-wide traceability of outlet-to-board relationships. An initial prototype was subjected to desktop-based functional tests to verify correct behavior under the expected input conditions and with the developed parametric families. Following calibration of the matching and assignment logic, a first compiled version of the Dynamo workflow was produced as the baseline implementation for subsequent evaluation and refinement.

3.3 Validation and Calibration

Building on the procedures outlined in Sections 3.1 and 3.2, the validation and calibration processes were designed to test the proposed workflow under realistic modeling conditions and to evaluate its operational performance against a conventional manual baseline. This assessment compared the standard Revit-based circuit assignment process, which relied on direct interpretation of CAD electrical documentation, with the automated implementations using Dynamo and Python. The primary performance indicators for this comparison were execution time and the number of misassignments identified during the review stage. A unified set of five real-world case studies from a data center project was selected, featuring outlet rows with varying densities and configurations. This selection aims to assess the workflow's stability across different input conditions. For each case study, a reference assignment was generated from the CAD documentation and used as a benchmark circuit-to-panelboard relationships.

Calibration was conducted before validation by performing desktop-based functional tests on an initial prototype. This was done to verify that the developed parametric families operated correctly with the expected input structure. Refinements focused on consolidating the matching and assignment logic to create a stable baseline workflow. Subsequently, the parameters were fixed to prevent any adjustments during the evaluation runs. To ensure comparability, manual timing excluded file preparation overhead and captured only the assignment activity, while automated timing measured the end-to-end script runtime. Accuracy was assessed by counting discrepancies identified during the review stage and comparing them with the reference assignment list. This approach enabled consistent reporting across cases and facilitated replication of the evaluation protocol.

4 Results

4.1 Proposed framework

Figure 1 presents the proposed framework for automating outlet-to-circuit assignment and circuit-to-panel connection in a BIM environment, based on information extracted from CAD drawings with AI assistance. The workflow starts by compiling the project's technical documentation, generating screenshots from the AutoCAD plan views, selecting rows or groups of outlets, and verifying the legibility of electrical symbols and annotations. This step is repeated until a consolidated image is obtained with sufficient resolution and the largest possible number of clearly identifiable elements. The consolidated image is then processed in Microsoft Copilot using structured prompts that guide the interpretation of annotations and symbols, enabling the identification of outlets and the extraction of the required attributes, outlet identifier, circuit, and panel, which are organized into a dataset exported in Excel format. In the automation stage, the Excel file is imported into Dynamo to locate the corresponding outlets in the Revit model, retrieve their spatial coordinates (X, Y, and Z), establish spatial ordering, and execute Python scripts that generate circuits and connect each outlet to its corresponding distribution board. The outcome is an updated BIM model in which the electrical assignment consistently reflects the information specified in the CAD drawings, reducing manual effort during circuiting and panel configuration.

4.2 Evaluation framework and algorithmic workflow

To rigorously evaluate the performance of the Python-based automated workflow for assigning electrical outlets to circuits in BIM environments, five real-world case studies from a data center project were defined. The evaluation compared the traditional manual procedure in Revit, which relies on direct interpretation of electrical CAD drawings, with the proposed automated solution. Execution time and the number of errors detected during the review stage were selected as in the literature as critical factors influencing BIM model reliability and efficiency in MEP disciplines. Figure 2 shows a representative row of outlets requiring circuit assignment, highlighting the high level of geometric and functional repetition that characterizes this configuration and that, under manual workflows, increases the likelihood of inconsistencies. This operational context is particularly relevant, as previous studies on BIM automation emphasize that the greatest efficiency gains occur in repetitive, rule-governed tasks driven by structured graphical information.

Algorithmic architecture comprises four clearly defined stages, as shown in Figure 2**Error! Reference source not found.**. In the first stage, the system automatically identifies outlet families within the BIM model and extracts their spatial coordinates (X, Y, Z). The second stage processes the Y-coordinate exclusively, which is critical in this case study, given the vertical arrangement of the outlets. Sorting these values in descending order establishes a spatial hierarchy consistent with the logic embedded in the original electrical drawings. Subsequently, a Python-based node filters secondary outlets, recognizing that they appear in paired configurations with primary outlets and that the study focuses only on assigning primary elements. The third stage automatically generates electrical circuits in Revit, associating each primary outlet with its corresponding circuit. In contrast, the fourth stage performs the bulk connection of all generated circuits to the selected panelboard, completing the workflow without manual intervention (see Figure 2). This sequential structure ensures traceability between extracted geometric data and electrical assignment decisions, directly addressing limitations reported in prior CAD–BIM interoperability solutions.

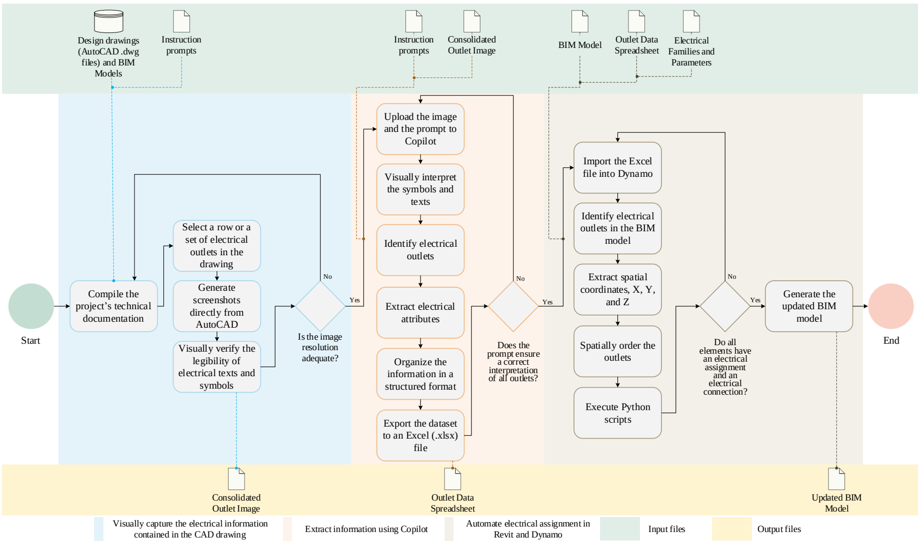

Figure 1. Proposed framework.

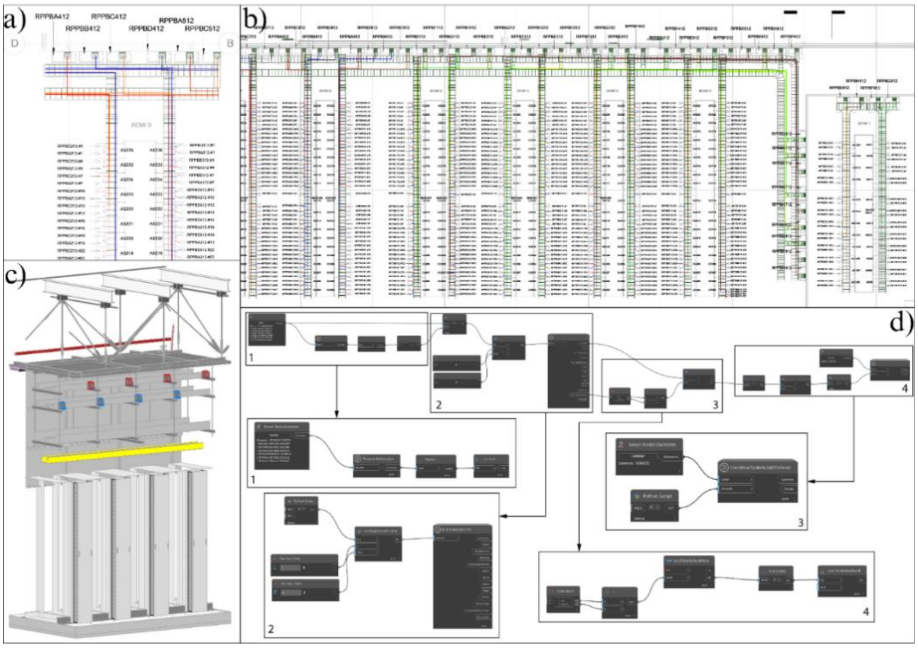

Figure 2. a) Row of outlets that must be assigned to a circuit. b) Number of sockets to be assigned to a circuit in the model. c) Dynamo Algorithm. d) Outlets are identified in blue and red.

4.3 Case study analysis and critical performance assessment.

The validation of automated BIM workflows requires empirical evidence that goes beyond proof-of-concept demonstrations and explicitly examines their behavior under realistic modeling conditions. In this context, the proposed AI-driven parametric workflow was evaluated through a unified set of five real case studies derived from a data center project, each representing rows of electrical outlets with varying densities, configurations, and operational constraints. The assessment compares the conventional manual circuit-assignment process in Revit, guided by CAD-based electrical documentation, with the automated solution implemented through Python scripts and Dynamo integration. Execution time and assignment accuracy were adopted as the primary performance indicators, since both metrics directly affect modeling efficiency, coordination reliability, and the quality of subsequent construction documentation (Table 22. Impact of AI-driven parametric automation on efficiency and accuracy in CAD–BIM electrical workflows.). The reported time corresponds exclusively to the circuit-assignment stage: manual assignment time in Revit versus the algorithm execution time once the input is available. The preparation of that input file, generated by the AI component after the extraction process, was not included in the measurement because prompt refinement represents a one-time, non-recurring calibration cost, while CAD image capture was also excluded because it is independent of the assignment process under analysis. The results reveal a consistent and substantial reduction in execution time when automation is applied, with gains increasing proportionally to the number of outlets involved. This behavior suggests that the algorithm exhibits favorable scalability characteristics, particularly in environments dominated by repetitive elements and a strict sequencing logic. In large outlet rows with more than 40 elements, the automated workflow effectively mitigates the cumulative delays inherent to manual selection, verification, and circuit creation, a limitation frequently reported in BIM-based electrical coordination studies.

In terms of accuracy and model reliability, the automated workflow performed consistently across all evaluated cases, although a slight discrepancy in Case 3 (48 outlets) indicates that minor variations may still occur under specific conditions. By contrast, the manual approach showed increasing inconsistencies as task repetition and dataset size grew, mainly due to incorrect circuit–panel associations, misinterpretation of CAD references, and omissions in repetitive assignments. Supported by geometric filtering, rule-based ordering, and parametric control, the deterministic algorithm produced consistent and reproducible outcomes that reduced human-induced variability. Although time savings were evident even in small-scale scenarios, the advantage of automation became more pronounced in larger datasets, where manual execution led to disproportionate increases in time and error risk. Unlike prior AI-assisted BIM approaches focused on isolated tasks, the proposed workflow integrates graphical interpretation, data processing, and circuit assignment into a unified pipeline, strengthening model consistency and supporting scalable electrical system modeling in complex BIM environments. Table 2 summarizes the case studies, comparing manual and automated methods by execution time and errors.

Table 22. Impact of AI-driven parametric automation on efficiency and accuracy in CAD–BIM electrical workflows.

Case Studies	# Outlets	Manual method		Automated method	
		Time (min)	Errors	Time (min)	Errors
Case 1	42	31.50	6	0.03	0
Case 2	24	12.20	2	0.02	0
Case 3	48	72.50	10	0.01	1
Case 4	12	8.32	1	0.02	0
Case 5	6	4.33	0	0.02	0

4.4 Comparative impact on efficiency, accuracy, and model reliability

Beyond improvements in execution time and error reduction, the comparative evaluation reveals structural limitations in prevailing electrical modeling automation approaches. Prior studies often focus on partial automation or decision-support systems that accelerate isolated tasks while maintaining manual interpretation during critical CAD–BIM translation stages. In contrast, the proposed workflow demonstrates that substantial performance gains arise when rule definition, geometric filtering, and assignment logic are fully formalized within a unified algorithmic process. This approach effectively decouples modeling effort from the number of elements, overcoming the efficiency decline commonly observed in manual and semi-automated BIM practices as task repetition increases.

From an accuracy perspective, the findings indicate an epistemic shift rather than a minor technical improvement. Manual workflows depend on continuous cognitive validation, introducing variability, fatigue-related errors, and inconsistencies that scale with repetition. While previous studies mitigate these issues through visual checks or post-processing validation, the proposed method embeds decision rules directly into the execution logic, eliminating interpretative ambiguity at its source. The results therefore challenge the assumption that human oversight is essential for correctness in complex electrical assignments, showing that deterministic, geometry-driven logic can outperform manual reasoning in highly repetitive and regulated design contexts.

The workflow also improves BIM model reliability compared with fragmented automation strategies reported in prior research. Whereas many studies automate extraction or classification without resolving downstream connectivity, the proposed approach ensures consistent outlet-to-circuit and circuit-to-panel relationships, producing a more stable, auditable, and reusable model for coordination, simulation, and operation. Overall, the results support viewing AI-driven and parametric CAD–BIM automation not merely as a productivity enhancement, but as a structural mechanism for enforcing design logic and reducing systemic uncertainty.

Conclusions

This study provides three main theoretical contributions. First, it proposes an end-to-end CAD-to-BIM automation workflow for electrical outlet assignment by integrating graphical capture, AI-assisted information extraction, structured data processing, and BIM-based parametric execution. Second, it defines the role of AI as a mechanism for converting unstructured electrical CAD information into structured datasets that support rule-based BIM automation while reducing manual interpretation. Finally, it introduces a reproducible rule-driven logic for outlet-to-circuit and circuit-to-panelboard assignment, demonstrating how repetitive MEP tasks can be formalized into deterministic BIM workflows that improve semantic consistency in model authoring.

The theoretical contributions of this study have practical applications in industry workflows. The proposed method integrates AI-based data structuring with Dynamo and Python scripting in Revit, significantly reducing the time for outlet and circuit assignments while enhancing consistency during model reviews. Validation through five case studies highlighted two representative tests: in the first, manual assignment of 42 outlets took 31.5 minutes with six errors, while the automated workflow completed it in 0.033 seconds without mistakes. In the second, the manual process for 24 outlets took 12 minutes with two errors, and the automated method finished in 0.025 seconds error-free. These results demonstrate a shift from expert-dependent processes prone to human error to a rule-based, structured input workflow, reducing rework and improving model reliability, especially in projects with repetitive electrical configurations.

Despite the contributions of this study, several limitations remain. The empirical assessment was based on two data center case studies with high geometric repetition and a spatial layout that enabled classification mainly along a single coordinate, which may restrict the generalizability of the findings to projects with more heterogeneous designs, multiple distribution logics, or different outlet-matching patterns. In addition, the proposed workflow depends on consistent outlet family identification and naming across CAD documentation, the AI-assisted structured dataset, and BIM parameters, so variations in drafting standards, screenshot quality, or prompt sensitivity may affect its robustness. The system also does not explicitly verify compliance with electrical engineering regulations, including circuit load capacity, load balancing, or conformity with applicable codes, as these were treated as predefined input conditions. Future research should therefore validate the approach across a wider range of building typologies and electrical design conventions, explore direct data extraction from CAD sources instead of image captures, incorporate automated checks for electrical rules and model consistency, and examine adoption-related aspects, including setup effort, script maintainability, and input governance at the organizational scale.

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