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Research Article

AI Agents for Automated Design and Compliance Verification in Buildings and Infrastructure: A Case Study Approach with No-Code/Low-Code Implementation

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Abstract

This study addresses the inefficiency and error-proneness of traditional manual compliance checks in the Architecture, Engineering, and Construction (AEC) sector. We present a case study methodology automating AEC design/compliance tasks (ASHRAE 62.1 ventilation, ADA accessibility, structural foundation sizing) using AI automations and agent-like components integrated into a No-Code/Low-Code (NC/LC) visual workflow platform. The approach includes embedded Large Language Model (LLM)-based Quality Assurance (QA/QC) checkpoints and utilizes Retrieval-Augmented Generation (RAG) to enhance reliability. Results demonstrate significant efficiency gains, reducing execution times by up to 99.9% post-setup versus manual methods, alongside high accuracy (0% error rate) from automated components compared to manual baselines (1.25-2.5% errors). LLM QA/QC effectively flagged discrepancies but showed minor inconsistencies (94-95% success rate), indicating its utility as an assistive validation layer requiring oversight. This research contributes empirical evidence for an integrated NC/LC and modular AI approach for diverse AEC compliance tasks, offers practical evaluation of embedded LLM validation, and presents necessary case study performance data. Limitations include the specific case studies/tools used and the controlled manual baseline.

The findings show a practical path for AEC firms to improve workflow efficiency, enhance accuracy, reduce risks, and democratize automation without deep programming expertise. Enabling more reliable compliance contributes to safer infrastructure and fosters innovation by potentially shifting professional roles.

Keywords: AI Agents; Automated Design; Automated Compliance; Buildings and Infrastructure; Digital Workflows; Human-AI Collaboration; No-Code/Low-Code Platforms; LLM Validation; RAG Compliance Verification.

Highlights

- AI automation via NC/LC achieves up to 99.9% time reduction and eliminates errors in AEC compliance tasks.
- Utilizing RAG enhances LLM-based QA/QC by ensuring traceable validation against specific regulations, though oversight remains key.
- No-Code/Low-Code platforms democratize AI, enabling AEC professionals to create custom automation tools without coding.

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1 Introduction

The Architecture, Engineering, and Construction (AEC) industry faces persistent challenges in accuracy, efficiency, and adherence to increasingly stringent regulations (SmartBrief, 2024). The sector's noted slow adoption of digital tools (Whatfix, 2024) creates systemic inefficiencies, particularly in design and compliance verification. Manual workflows, characterized by laborious interpretation of dense regulatory texts and 2D drawings, are frequently slow, inconsistent, and susceptible to error. These issues contribute to project delays, cost overruns, and design deficiencies, often linked to inadequate experience, poor coordination, or ineffective knowledge transfer (Aslam & Umar, 2024). Specific bottlenecks include cumbersome document creation and management, inefficient review cycles, and difficulties in cross-referencing requirements (Zou et al., 2023).

While Building Information Modelling (BIM) established a crucial digital foundation by providing structured data, it has not fully resolved these underlying workflow challenges (Zou et al., 2023). Significant hurdles remain in translating complex, ambiguous regulatory language into computable logic and ensuring the consistently detailed models required for reliable automated checking.

Artificial Intelligence (AI) is emerging as a transformative force, reshaping traditional practices. AI tools, particularly when integrated within accessible No-Code/Low-Code (NC/LC) platforms, offer a promising path forward. This synergy automates repetitive, rule-based tasks like code lookup, calculation, and validation, freeing professionals to focus on higher-value creative and problem-solving activities. NC/LC environments democratize the creation of these automated solutions, enabling domain experts without deep programming skills to build and manage tailored workflows (DevOps, 2025). This aligns with broader industry trends toward automation and digital transformation, driven by demands for improved productivity and efficiency.

However, the adoption of AI, especially Large Language Models (LLMs) used for design development and interpreting regulations, introduces challenges regarding reliability, validation (such as mitigating hallucination risks), and accountability. Ensuring trust in these systems within safety-critical applications is paramount (Emaminejad et al., 2022).

This study demonstrates a practical, NC/LC-based approach using AI automations and agent-like components to automate specific AEC design calculation and compliance verification tasks, incorporating embedded LLM-based validation. It aims to address the need for accessible, efficient, and reliable design and compliance tools. We investigate performance through three common AEC case studies: ASHRAE 62.1 ventilation calculations, ADA accessibility compliance checks, and preliminary structural foundation sizing. Our methodology utilizes a visual workflow platform (n8n, 2025) integrated with LLM components and Retrieval-Augmented Generation (RAG) for enhanced design and QA/QC (Bali, 2024). This research addresses the following questions: (1) Can AI components in NC/LC tools accurately automate these AEC tasks? (2) How do they compare to manual methods in speed and accuracy? (3) How effective are embedded LLM QA/QC strategies? (4) What are the practical implications for AEC workflows?

Findings suggest significant efficiency gains and improved consistency are achievable, paving the way for AI to become a trusted collaborator in design and compliance, while highlighting the ongoing necessity for human oversight (Graydon & Lehman, 2025). The drive towards such automated solutions is also evidenced by real-world initiatives aiming to streamline regulatory processes.

2 Literature Review / Conceptual Basis

This section establishes the study's theoretical foundation by defining key concepts, reviewing relevant theories, identifying research gaps, and outlining the conceptual model.

2.1 Defining Key Concepts

This study integrates several key technologies and concepts within the AEC context:

- AI Implementations: AI integration in AEC workflows spans from automation to autonomous agents. This study explores components across this range:

1. Traditional Automation: Structured, predefined workflows executing specific tasks reliably, sometimes enhanced by AI (e.g., for data extraction) and recently made more accessible via NC/LC platforms. Suitable for critical processes demanding high fidelity.
2. Dynamic AI Automation: Workflows where AI analyses data to select between predefined paths, adding flexibility (e.g., conditional routing based on compliance checks).
3. AI Agents: Software systems exhibiting greater autonomy to perceive inputs, reason, and act towards defined goals, offering adaptability but requiring robust validation due to potential variability.

- No-Code/Low-Code (NC/LC) Platforms: Visual development environments enabling users with minimal or no coding expertise (often domain experts) to build applications and automate processes using drag-and-drop interfaces and pre-built components (SAP, n.d.). They empower professionals to create custom automation workflows, accelerating digital tool adoption.
- Automated Design Calculation: The use of digital tools to perform engineering computations based on established formulae and guidelines (e.g., ASHRAE standards, structural principles), improving speed and reducing manual calculation errors common in AEC.
- Automated Compliance Verification (ACV): Programmatically checking designs or data against regulatory codes and standards (Mendonça & Ferreira, 2024; Zou et al., 2023). While various ACV techniques exist (rule-based, graph-based, AI), challenges remain, particularly in interpreting complex regulations and ensuring system reliability.
- Large Language Models (LLMs): AI models trained on vast text datasets, capable of understanding natural language, generating human-like text, and performing reasoning tasks. Their application in AEC is nascent but promising for ideation and interpreting complex regulatory documents. However, they are known to produce plausible but incorrect information "hallucinations", raising significant concerns about their fitness for safety-critical applications without rigorous validation (K2View, 2024; Graydon & Lehman, 2025).
- LLM Validation and QA/QC: Essential processes to ensure the reliability and accuracy of LLM outputs, particularly in safety-critical applications like AEC compliance. This involves strategies to mitigate risks like hallucination and assess trustworthiness.
- Retrieval-Augmented Generation (RAG): An AI technique designed to improve LLM accuracy and reduce hallucinations by grounding responses in specific, relevant information retrieved from a trusted external knowledge base (e.g., a database of current building codes) before generation (Bali, 2024). This is crucial for ensuring compliance checks reference authoritative sources and overcome limitations like outdated training data inherent in general LLMs.

2.2 Existing Theories and Frameworks

This research is informed by theories related to technology adoption, digital transformation, and human-computer interaction:

- Technology Acceptance: Models like TAM and UTAUT (Venkatesh et al., 2003) suggest adoption hinges on perceived usefulness, ease of use (effort expectancy), and social influence. For AI in

AEC, user trust is a critical mediating factor influenced by system reliability and transparency (Emaminejad et al., 2022).

- Digital Transformation: AEC is undergoing a shift from basic digitization towards broader transformation (Agrawal et al., 2023). NC/LC platforms enabling expert-led AI development accelerate this, addressing the sector's noted slower adoption rates (Stanton Chase, 2024).
- Human-AI Collaboration & Explainability: Effective integration requires designing for trust, transparency, and appropriate oversight (Endsley, 2017; Marusich et al., 2024). Explainable AI (XAI) techniques and Uncertainty Quantification (UQ) are vital for making AI reasoning understandable and signalling when human judgment is needed, particularly for safety-critical decisions.
- Levels of Automation (LoA): Frameworks characterizing the degree of autonomy in systems help classify AI implementations (Rafizadeh et al., 2024). Defining the appropriate LoA for different AEC tasks is crucial for effective human-AI work division (Altavilla & Blanco, 2020).

2.3 Knowledge Gaps and Research Opportunities

Despite growing interest in AI and automation for AEC, several gaps remain:

- Lack of Integrated NC/LC + AI Compliance Solutions: While ACV and NC/LC are studied (Yamusa et al., 2024), there is limited research demonstrating integrated solutions using modular AI components within accessible NC/LC platforms for diverse AEC compliance tasks.
- Need for Practical LLM Validation Methods in AEC: General LLM risks are known, including hallucination (Emaminejad et al., 2022), but practical, embedded validation mechanisms (like LLM-based QA/QC using RAG) specifically evaluated within AEC compliance workflows are underexplored especially given the critical perspective that LLM outputs require robust verification before use in high-stakes engineering contexts (Graydon & Lehman, 2025).
- Scarcity of Empirical Evidence: Beyond theoretical possibilities, there is a need for empirical data from case studies showing the real-world performance, usability, and workflow implications of integrated AI/NC-LC systems in specific AEC scenarios.

2.4 Proposed Conceptual Model

This study utilizes a conceptual model (illustrated in the Methodology section, Figures 1 & 2) implemented within an NC/LC platform. The model comprises: (1) User Inputs (e.g., design parameters, digitized code excerpts); (2) NC/LC Platform n8n for workflow orchestration; (3) Modular AI Automations/Agents performing specific tasks (ASHRAE, ADA, Structural calculation/checking) including using RAG to extract relevant regulations; (4) An LLM Validation Checkpoint using RAG and comparative checks for QA/QC; (5) Outputs (compliance reports, calculated values) designed for human review and potential intervention. This architecture emphasizes modularity, accessibility via NC/LC, embedded validation (addressing Gap 2), and human oversight, aligning with HCI/Trust principles and enabling empirical assessment (addressing Gap 3) of an integrated solution (addressing Gap 1).

3 Methodology

This methodology details the framework used to develop, implement, and evaluate the AI automations and agent-like components. The work was conducted within an NC/LC platform for AEC design calculation and compliance verification, aligning with the conceptual model presented in Section 2.4.

3.1 Research Design

This research uses a case study-driven methodology to evaluate the feasibility and performance of modular AI components within an NC/LC workflow automation platform. This approach allows for exploring complex processes through replicable scenarios with representative AEC tasks. The three case studies—ASHRAE 62.1 ventilation calculations, ADA accessibility compliance checks, and structural foundation sizing—were specifically chosen because they represent simple, familiar design and compliance tasks within the AEC industry. This selection demonstrates how NC/LC tools can automate routine work without requiring deep AI expertise, making the benefits of this approach tangible and accessible. Quantitative comparisons focused on task completion time and error rates between a controlled manual baseline and the automated workflows. Qualitative assessment focused on the effectiveness of an embedded LLM-based validation layer for QA/QC.

3.2 System Development and Tools

We developed the system using n8n, a fair-code, visual workflow automation tool. We selected it for its flexibility in handling complex logic (conditionals, loops, error handling), its customization options with Python and JavaScript integration, its AI-powered development assistance (the "AskAI" feature), and its self-hosting capability for data control. The tool's open-source nature and active community support were also key factors. Key AI components developed as modular n8n nodes/sub-workflows included:

- ASHRAE 62.1 Component: Calculated required ventilation rates based on ASHRAE 62.1 section 6.2, using input room parameters (area, occupancy) and referencing digitized standard tables through Google Sheet Lookup. Standard tables were manually converted into a Google Sheet format.
- ADA Compliance Component: Implemented via two distinct methods for comparison:
- Method 1 (OCR + LLM Extraction): Utilized an OCR service (via Mistral API) to process the ADA 2010 standard PDF, followed by an LLM information extractor prompted to extract specific dimensional requirements (e.g., door widths, clearances) for comparison against design.
- Method 2 (RAG Approach): Leveraged Retrieval-Augmented Generation. The ADA 2010 standard text was vectorized and stored in Pinecone. An LLM agent was prompted with the design scenario (e.g., manual swinging door dimensions), queried the Pinecone vector store to retrieve relevant ADA clauses, and then used the retrieved text to perform the compliance check. LLM query sent to validate the accuracy of the retrieved clauses from vector space.
- Structural Foundation Sizing Component: Performed preliminary sizing calculations for a square footing based on user inputs (dead load Gk, live load Qk, allowable bearing pressure q_allow) following Eurocode 7 / UK practice principles.
- LLMs Tested: We tested multiple LLMs via API for various components and validation steps—including OpenAI (GPT-4o-mini), Google (Gemini 2.0), and DeepSeek (deepseek_chat)—to assess performance differences. Older/other models showed poor reliability in initial tests.

3.3 Integration Methodology

Components were integrated within n8n workflows. Key steps involved:

- Knowledge Base Preparation: Digitizing relevant code excerpts (ASHRAE tables, ADA 2010) into accessible formats (Google Sheets, Markdown). For the RAG method, ADA text was chunked, vectorized using OpenAI embeddings (text-embedding-3-small), and stored in Pinecone.
- Data Input/Output: Using Google Sheets and simple forms for managing input parameters and storing output results.
- API Connections: Utilizing n8n's HTTP Request nodes to connect to external APIs for LLMs, OCR services, and the Pinecone vector database.
- Workflow Orchestration: Designing the sequence of operations (trigger -> input gathering -> AI component execution -> LLM validation step -> comparison/logic -> output generation) using n8n's

interface, including conditional 'IF' nodes and 'Looping' nodes for batch processing multiple rooms/doors. Figures 1 and 2 illustrate samples of workflow implementations.

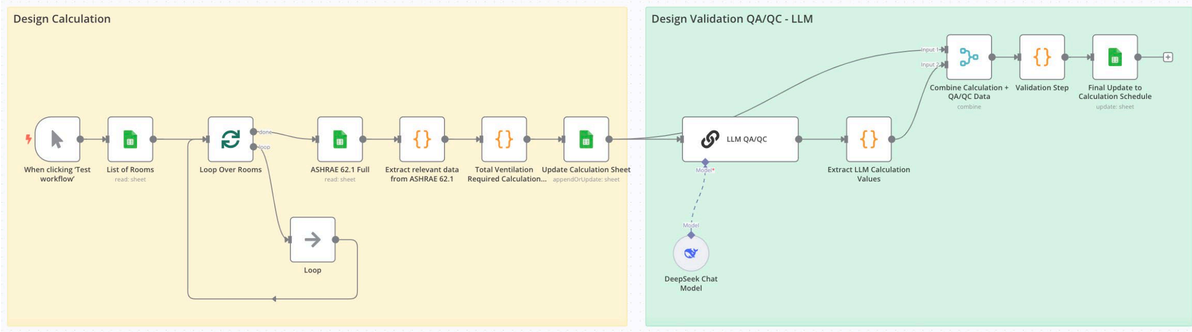

Figure 1. The n8n workflow for ASHRAE 62.1 calculation and validation. The 'Design Calculation' stage (yellow) automates the ventilation calculation based on input data. The 'Design Validation QA/QC-LLM' stage (green) uses a separate LLM call to independently verify the result and flag discrepancies.

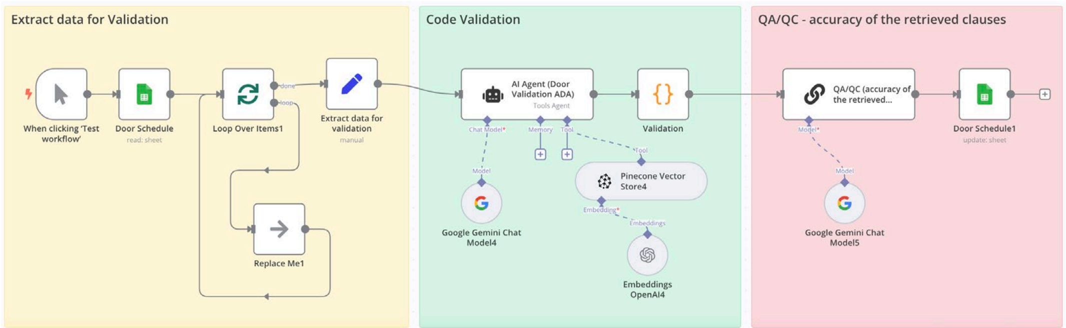

Figure 2. The n8n workflow for ADA compliance using a Retrieval-Augmented Generation (RAG) approach. The 'Code Validation' stage (green) uses an AI Agent and Pinecone vector store to retrieve relevant ADA clauses for the compliance check. The 'QA/QC' stage (red) then uses a separate LLM call to verify the accuracy of the retrieved clauses.

3.4 Case Studies Scenarios

Three distinct and representative AEC scenarios were defined:

- ASHRAE: Classroom, 100 m^2, 35 occupants (Standard: ASHRAE 62.1-2022).
- ADA: Manual Swinging Door with specific dimensions/clearances (Standard: ADA 2010).
- Structural: dead load (Gk) = 700kN, live load (Qk) = 600 kN, allowable bearing pressure (q_allow) = 240 kPa (Standard: Eurocode 7 / UK practice).

3.5 LLM Validation, Sanity Check and QA/QC Protocols

An LLM-based validation/sanity check step was incorporated:

- For ASHRAE and Structural cases, the output from the primary calculation component was compared against an independent calculation performed by a separate LLM call using the same input data.
- For ADA Method 1 (OCR), validation focused on manually verifying the accuracy of the LLM's extraction of requirements from the OCR'd text. For ADA Method 2 (RAG), validation relied on assessing the accuracy of the retrieved clauses and the LLM's reasoning based on them.
- Discrepancies identified by the automated comparison or manual checks triggered flags indicating a need for human review.
- Hallucination mitigation strategies included structured prompt engineering (requesting step-by-step reasoning or specific output formats), using RAG to ground ADA checks in source text, and implementing error handling nodes to manage mismatches during the validation comparison.

3.6 Data Analysis

Metrics included task completion time and error counts/types (manual vs. automated). Manual baselines were established by an engineer, with automated times/results logged by n8n and compared against ground truth. LLM sanity check results provided an internal QA metric. Analysis involved tabulating data, calculating mean differences (%), and using visualizations for comparison.

3.7 Ethical Considerations

No personal or proprietary project data was used; scenarios were synthetic or anonymized. We followed responsible AI practices emphasizing transparency and accountability.

4 Results- Key Findings

This section presents the quantitative findings from the three case studies comparing manual workflows against the developed AI automations and agent-like components, focusing on task completion time, accuracy, and LLM validation outcomes. Automated execution times reported reflect workflow processing after the initial setup phase; setup times (ranging from 1.5 to 4 hours per workflow) are noted separately as they represent an initial investment recouped through repeated use.

4.1 Case Study 1: ASHRAE 62.1 Ventilation Results

The automated workflow for calculating ventilation rates for 80 rooms demonstrated significant efficiency gains. Post-setup execution time was reduced by approximately 99.7% compared to the manual baseline. Furthermore, the automated component eliminated calculation errors observed in the manual process (0% error rate vs. 1.25%). The integrated LLM sanity check identified four discrepancies during testing, indicating a 95% success rate for this QA/QC step in this scenario. Detailed results are presented in Table 1.

Table 1. ASHRAE 62.1 Ventilation Calculation Results Summary

Metric	Manual Baseline	Automated Workflow
Execution Time (80 rooms)	16 hours (960 min)	3 minutes
Initial Setup Time	N/A	3 hours (180 min)
Time Reduction (Post-Setup)	N/A	99.7%
Error Rate (Calculations)	1.25% (1/80 rooms)	0%
LLM Sanity Check Error Rate	N/A	5% (4/80 rooms flagged)

4.2 Case Study 2: ADA Compliance Results

In the 80-door ADA compliance check scenario, both automated methods substantially saved time and improved accuracy over manual checks. Automated execution time fell by 99.8-99.9%, while accuracy improved from 97.5% (manual) to 100% (automated). Method 1 (OCR + LLM Extraction) had a shorter setup time in this instance, while Method 2 (RAG) offered enhanced traceability by grounding compliance checks in retrieved code clauses. A summary of these results is shown in Table 2.

Table 2. ADA Compliance Check Results Summary

Metric	Manual Baseline	Automated (Method 1: OCR)	Automated (Method 2: RAG)
Execution Time (80 doors)	18 hours (1080 min)	2 minutes	1.5 minutes
Initial Setup Time	N/A	3 hours (180 minutes)	4 hours (240 minutes)
Time Reduction (Post-Setup)	N/A	99.8%	99.9%
Accuracy (Compliance Check)	97.5% (2 errors/80)	100%	100%
Key Dependency	Human Judgment	OCR + LLM Parsing	Clause Retrieval (RAG)
LLM Sanity Check Error Rate	-	-	6% (5/80 doors flagged)

4.3 Case Study 3: Structural Foundation Sizing Results

The automated workflow for preliminary structural foundation sizing demonstrated significant execution time savings, reducing the time per check by approximately 96.7% post-setup compared to the manual method. Initial tests showed the automated component matched manual accuracy (100% correct). The LLM sanity check showed high consistency over 20 repeated runs, flagging one inconsistency (95% success rate). Table 3 provides these results, also noting that the initial setup time exceeds the time required for a single manual check, emphasizing the need for repeated use to realize efficiency benefits.

Table 3. Structural Foundation Sizing Results Summary

Metric	Manual Baseline	Automated Workflow
Execution Time (Per Check)	15 minutes	30 seconds
Initial Setup Time	N/A	1.5 hours (90 min)
Time Reduction (Post-Setup)	N/A	96.7%
Accuracy (Initial Test)	100% (0% error)	100% (0% error)
LLM Consistency; Sanity Check Error Rate (20 runs)	N/A	5% (1/20 runs flagged)
Note:	N/A	Setup time > manual time for single use.

5 Discussion

The findings offer valuable insights into the application and impact of integrating AI automations and agent-like components within NC/LC platforms for AEC design and compliance workflows.

5.1 Interpretation of Key Findings

The results directly address the research questions. (RQ1 Accuracy): The high accuracy (0% error rate) of automated components on RAG and rule-based tasks confirms their potential fidelity, aligning with literature on automation reducing human error. However, the LLM validation component's limitations (5-6% inconsistency, observed as minor calculation drifts during testing) underscore the need for human oversight in safety-critical applications, despite its utility in flagging issues. This aligns with broader concerns regarding LLM fitness for high-stakes engineering tasks without rigorous verification. The ADA case highlighted dependencies, with RAG offering slightly better grounding than OCR/extraction for reliability. (RQ2 Speed): Dramatic post-setup execution time reductions (up to 99.9%) confirm the potential efficiency for repetitive tasks and help address noted AEC productivity gaps, consistent with ACV literature (e.g., Yamusa et al., 2024). However, the significant setup time highlights the effort-expectancy trade-off relevant to adoption models (Venkatesh et al., 2003; Emaminejad et al., 2022). (RQ3 LLM QA/QC): Embedded LLM checks proved partially effective, identifying discrepancies and enhancing traceability via RAG, supporting HCI/XAI principles (e.g., Endsley, 2017; Marusich et al., 2024; Emaminejad et al., 2022). Yet, observed inconsistencies confirm LLMs currently serve best as assistive QA layers, not infallible validators, particularly for calculations where tool augmentation shows promise (Goodell et al., 2024), aligning with known LLM limitations (K2View, 2024). (RQ4 Implications): Collectively, results suggest potential workflow transformation through enhanced speed and accuracy, alongside the need for careful implementation strategies involving human oversight and the democratizing potential of NC/LC, potentially mitigating skills gap issues by empowering domain experts.

5.2 Comparison with Literature and Theory

Findings align with research showing ACV efficiency benefits (Yamusa et al., 2024; Aslam & Umar, 2024) and real-world initiatives driving towards automated compliance, while the setup time highlights potential adoption barriers (Venkatesh et al., 2003; Emaminejad et al., 2022). The successful NC/LC implementation supports democratization arguments (SAP, n.d.) and contributes empirically to digital transformation literature (Agrawal et al., 2023), addressing the gap between specialized ACV tools and accessible platforms (Yamusa et al., 2024; Stanton Chase, 2024). LLM validation results offer practical insights complementing HCI/XAI literature on trust and transparency (Endsley, 2017; Emaminejad et al., 2022; Marusich et al., 2024). This is particularly relevant given the identified lack of systematic research into trust dimensions like reliability and safety for AI within the specific AEC context. The findings also reinforce awareness of LLM risks including hallucination (K2View, 2024; Bali, 2024), addressing the gap regarding practical validation methods for AEC. This study provides needed empirical evidence from case studies, filling another identified gap.

5.3 Implications of the Study

The practical implications for AEC include significant potential for improved productivity via automation of routine compliance/design tasks, reduced risk through enhanced accuracy, and democratization of advanced tools via NC/LC platforms empowering domain experts. This necessitates a shift in professional roles towards AI oversight and higher-level problem-solving. Theoretically, the study provides empirical context for AI adoption, digital transformation, and human-AI collaboration models in AEC. Critically, it underscores the need for robust, embedded validation strategies when deploying LLMs in safety-critical applications. This also highlights the need for clear governance frameworks and reinforces professional accountability in AI-assisted workflows.

5.3.1 Societal & Institutional Adoption Pathways

The widespread adoption of AI tools in AEC requires a multi-faceted approach addressing governance, liability, and workforce evolution. Professional and regulatory bodies must collaborate to create governance frameworks that include standards for machine-readable digital submissions and certified protocols for auditing AI-assisted designs to ensure public safety and transparency. The use of AI also raises complex questions about professional liability, as an erroneous output could create a chain of liability involving multiple parties. This necessitates an evolution of industry standards and contracts to clarify roles, responsibilities, and accountability in human-AI workflows. Furthermore, as AI automates repetitive tasks, the workforce must adapt through upskilling and retraining in digital literacy and AI oversight to transition from performing manual tasks to managing and validating automated systems.

5.4 Limitations of the Study

While this study provides valuable insights, several limitations should be acknowledged when interpreting the results. Limitations influencing generalizability include the scope (three specific case studies), dependency on the specific tools used (n8n, selected LLMs/APIs), a controlled manual baseline comparison, which may not fully capture real-world variability due to differing expertise or time pressures, inherent LLM reliability factors (consistency, updates), and the setup time investment required.

5.5 Future Research Directions

Future work should expand the scope to more complex compliance scenarios and diverse AEC tasks. Developing and testing more robust LLM validation techniques including RAG for direct parameter retrieval and tailored for AEC, conducting comparative analyses of different NC/LC platforms and AI models, performing longitudinal studies in real firms to assess adoption and scalability, deeper investigation of human-AI collaboration dynamics, and exploring integration with real-time data sources (e.g., IoT, digital twins, developing multi-agent systems, leveraging knowledge graphs, and investigating pathways towards AI as autonomous design advisors are key directions.

6 Conclusions

This paper demonstrated the successful implementation and evaluation of AI automations and agent-like components within a No-Code/Low-Code (NC/LC) platform for automating specific AEC design calculation and compliance verification tasks (ASHRAE 62.1, ADA, structural foundation sizing). The key findings confirmed that this approach yields significant efficiency gains (up to 99.9% reduction in post-setup execution time) and high accuracy for RAG and rule-based tasks compared to manual methods, addressing persistent industry challenges in productivity and error reduction.

This paper provides case-study evidence on the practical application of integrated NC/LC and AI solutions in AEC compliance, filling identified gaps regarding accessible automation tools and practical validation methods. The embedded LLM-based QA/QC strategy proved partially effective, highlighting its potential as an assistive validation layer while simultaneously underscoring the critical need for robust verification protocols (potentially using RAG) and continued human oversight in safety-critical applications due to inherent LLM limitations.

The broader implications suggest a viable pathway for democratizing advanced automation in AEC firms, empowering domain experts through NC/LC tools and potentially reshaping professional roles towards higher-level oversight and problem-solving. For this transition to succeed, future work must address the critical need for clear governance frameworks and policies that can manage professional liability and guide regulatory integration. While acknowledging limitations related to scope and specific tools used, this research highlights the potential for these technologies to enhance efficiency, reduce compliance risks, and foster innovation. Ultimately, responsibly harnessing AI requires balancing automation benefits with rigorous validation and sustained human judgment to ensure the safety and reliability of the built environment.

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Conflicts of Interest
The authors declare no conflict of interest.

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