Communication in Physical Sciences, 2023, 9(4): 1232-1246

Architectural Technology and AI-Enabled BIM Compliance: A Global Framework for Cognitive, Self-Governing Regulatory Ecosystems

Kelechi Chigbu

Received: 14 July 2023/Accepted: 10 September 2023/Published: 19 September 2023

Abstract: *The first major digital transformation of the architecture and construction industry is the transition from a manual drafting process to an extremely complex environment of building models that contain lots of building data – Building Information Modeling (BIM). But keeping these complex and detailed digital models accurate and sound to meet strict regulation requirements is still extremely manual, with an increased risk of project delays, human error, and expensive delays. This paper proposes to create an AI-powered BIM Compliance Ecosystem that can link these two areas together. The proposed architecture combines the different functionality of cognitive computing, natural language processing (NLP), the knowledge graph and the open data standards (such as IFC) to convert the building codes, which are highly unstructured, to machine-readable semantic logic. It is a comparative study and places in parallel varying levels of maturity and artificial intelligence and of regulatory complexity – deterministic codes, prescriptive codes, open-ended performance based standards. Furthermore, it addresses critical problems like data interoperability, professional liability, and the need for Explainable AI (XAI) in order to make AI transparent in design. The results of this study ultimately offer a roadmap - based on empirical data - to inform and support future prototyping and simulation testing, as well as the rollout of self-governing architectural compliance frameworks across the industry.*

Keywords: *Architectural Technology, Artificial Intelligence (AI), Automated Compliance Checking, Building Information Modeling (BIM), Industry Foundation Classes (IFC), Natural Language Processing (NLP)*

Kelechi Chigbu
Huckabee College of Architecture, Texas Tech University, Lubbock, Texas, USA
Email: kelechi.chigbu.design@gmail.com

1.0 Introduction

The architectural and construction industry has been undergoing an extraordinary digital transformation over the past few years, where the use of 3D modelling software such as BIM (Building Information Modelling) has replaced the traditional manual drawing, turning a highly data-centric space (Aydın & Yaman, 2020). This paradigm shift is a transition from the 2D representation of images to multidimensional digital prototypes with a large amount of geometric, material and semantic information (Lee *et al.,* 2021). In today's architectural technology, BIM is a common source of information, in which the stakeholders can visualize, simulate and analyse how the building will perform throughout its life (Amor & Dimyadi, 2021). But, as digital models become ever more sophisticated, so have the methods for validating such designs against regulatory requirements (Ding *et al.,* 2022).

Even with all the capabilities of modern BIM platforms, compliance checking still heavily relies on traditional and manual workflows that are a significant constraint in the project lifecycle (Amor & Dimyadi, 2021). A lot of time and resources are spent by architects and project managers manually wading through the mountains of information contained in complex building codes, zoning bylaws and life-safety regulations (Aydın & Yaman, 2020). This manual verification is inherently labour intensive, highly susceptible to human errors and may result in costly redesigns, major project delays and lengthy regulatory approval cycles (Amor & Dimyadi, 2021). Building codes, however, are sometimes not clear-cut and can be complex and frequently change, which is too slow for today's changing design (Ding *et al.,* 2022).

This is where the AI imperative comes in, as the capabilities of machine learning, natural language processing (NLP), and computer vision (CV) are increasingly adopted into BIM processes, resulting in a pressing demand for AI solutions to overcome these inefficiencies (Ekanayake *et al.,* 2021). The first generation of automated rule checking tools attempted to digitise compliance, but suffered from inflexible compliance rules that were hardcoded and did not have the capability to comprehend nuanced rules, performance-based rules and the like (Solihin *et al.,* 2020). The use of state-of-the-art artificial intelligence enables systems to interpret unstructured regulatory text, capture intricate semantic relationships, and automatically cross-reference spatial models with the legal requirements (Zhong *et al.,* 2020). This is further improved by machine learning models and computer vision algorithms, which can break down 3D design components and detect spatial clashes, accessibility issues, and structural non-conformities (Hu *et al.,* 2023).

This conceptual paper further expands on this technological convergence, challenging to develop a complete theoretical model of an AI enabled BIM compliance ecosystem. Topics discussed include aspects of structural translation of textual building regulations to machine readable logic (Wu *et al.,* 2021), integration of cognitive computing and open BIM data standards like Industry Foundation Classes (IFC) (Lee *et al.,* 2021), and real-time design feedback loops (Peng & Liu, 2023). The paper addresses the current deficiency of research on how cognitive agents and semantic databases interact in an automated regulatory governance framework while systematically analyzing the architecture of the interaction. In addition, the paper explores nuanced differences between prescriptive and performance-based regulatory codes and their links to the maturity of AI (Amor & Dimyadi, 2021). It explores an ambiguous spatial constraint problem that is not easily solved by traditional rule engines, and looks at how to solve the problem using deep learning architectures and knowledge graphs (Hu *et al.,* 2023). This is a focused evaluation in which the discussion encompasses both technical capacity and the entire range of operation of autonomous validation systems in professional architectural activity.

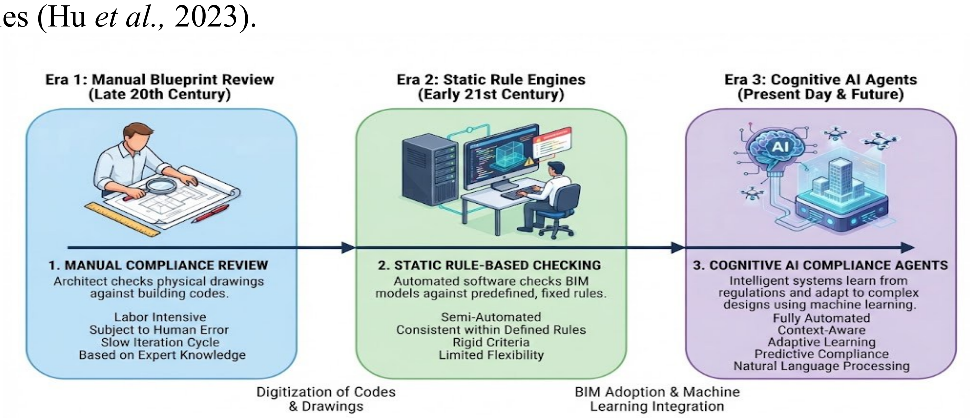

Fig. 1: Evolutionary Timeline of Compliance Checking (Zhang & El-Gohary, 2022)

Finally, the study tackles the key issues, challenges and ethics in moving towards a cognitive compliance setting. It includes discussion of challenges such as data interoperability (Lee *et al.,* 2021), legal liability for using an AI-validated model when the model is incorrect in on-site inspections, and the critical need for Explainable AI (XAI) to ensure transparency of the design (Love *et al.,* 2023). The paper brings these elements together to present an empirical research roadmap to spur future prototyping, simulation testing, and industry adoption of automated compliance frameworks (Shrestha, 2021).

2.0 Theoretical Foundations and Literature Synthesis

The principle change for modern architectural technology is an underlying shift from older computer-aided design (CAD) systems to an integrated, intelligent digital environment (Deng *et al.,* 2021). The first generation of digital tools mostly mimicked the way people manually drafted two dimensions, with limited data connectivity – just lines and text comments. Today, however, contemporary architectural practice is almost exclusively based on Building Information Modeling (BIM), where digital artifacts are conceived as smart, object-oriented, rich with spatial, material and temporal attributes (Yang *et al.,* 2021). This paradigm shift allows multi-disciplinary collaboration, lifecycle tracking, and deep simulation capabilities that are transforming how architectural projects are conceptualized and delivered (Deng *et al.,* 2021).

One of the key features of these modern information modeling frameworks is the ability to represent semantic data structures. BIM environments is a novel way of modeling that differs from traditional geometric models by linking physical building elements, including walls, structural columns, HVAC, fenestrations, etc., to functional attributes, performance parameters and relational hierarchies (Bloch & Sacks, 2020). This object intelligence inherently propagates changes throughout the project repository from one view or object. Therefore, architectural technology serves as a single source of truth, reducing difference between design intent and spatial coordination (Ren & Zhang, 2021).

While all the benefits of individual BIM platforms exist, the intelligent design trend is greatly dependent on the universal interoperability standards, which includes Industry Foundation Classes (IFC) (Ren & Zhang, 2021). IFC is an open, neutral data format, which allows the exchange of architectural information without proprietary restrictions between different software applications (Fan *et al.,* 2019). IFC offers a standardized framework for encoding building elements and their semantic relations, making it the backbone for sophisticated automated analysis, cross-platform data transfer, and mass-scale regulatory verification (Ren & Zhang, 2021).

On top of this digital landscape, a methodology called Automated Rule-Checking (ARC) has significantly proved to be essential to validate BIM models with building codes, safety standards, and zoning regulations (Fan *et al.,* 2019). Early commercial systems and Academic prototypes used to evaluate geometric and spatial features by hardcoded algorithmic rules with respect to prescriptive legal criteria (Fan *et al.,* 2019). These first generation systems have been successful in proving that corridor widths, fire exit distances, stair dimensions and other routine compliance checks could be calculated much faster than by hand (Fan *et al.,* 2019).

Despite their initial achievements, legacy Automated Rule-Checking systems have significant structural restrictions, especially when faced with unstructured and performance based regulations (Zhang & El-Gohary, 2021). Traditional ARC engines are used to work with parameters that are well-defined, and they're simply not the type of engine that can be used to interpret ambiguous legal text, qualitative safety requirements, or jurisdiction-specific nuances (Guo *et al.,* 2021). Hardcoded rule sets are hard to maintain when the building code changes or is revised since they should be manually re-written and re-validated, thereby affecting design agility and preventing the scalability of the automated compliance method (Zhang & El-Gohary, 2021).

The Architecture, Engineering, and Construction (AEC) sector is exploring beyond traditional rule checking engines to Artificial Intelligence to be the powerful catalyst for change (Bloch & Sacks, 2020). AI–based approaches provide cognitive flexibility to digital processes and enable systems to learn from past compliance data, to infer spatial relationships, and to process more complex geometric interactions, which are much harder to solve with fixed approaches (Buiten, 2019). This kind of integration transforms the mode of passively storing information on the architectural design to an active and intelligent governance mode for architectural design, which can change with the complex regulatory conditions (Abioye et al., 2021).

Cognitive computing and Natural Language Processing (NLP) are crucial components to this AI integration, serving a vital role in converting human language to machine action. Building regulations are typically written in a way that is similar to normal legal language, with many conditional clauses, exceptions and qualitative standards (Zhou *et al.,* 2022). These regulatory documents can be interpreted by advanced NLP architectures, which can also automatically convert static legal prose into dynamic compliance rules, by extracting the essential constraints of the law (Zhang & El-Gohary, 2021).

Knowledge graphs, in conjunction with NLP, have an irreplaceable role in architectural compliance in drawing a map of the complicated dependency that exists in architectural compliance (Guo *et al.,* 2021). Multifaceted relationships between multiple spatial layouts, structural loads, environmental controls, and municipal codes are found in building projects (Fang *et al.,* 2020). This information is made into nodes and edges connected to form the vast network, which enables the AI models to contextually reason about the design configuration over knowledge graph. This fusion of cognitive computing and NLP, with knowledge graphs, forms the theoretical foundation for the realization of truly autonomous, adaptive BIM compliance ecosystems in the present day.

3.0 Proposed Conceptual Framework and Core Propositions

This conceptual framework offers a holistic blueprint to change compliance verification and make this melding of architecture tech and AI a reality. The proposed architecture exceeds the current state of the art automated checking tools and establishes an agent-driven environment, which continuously interacts with the digital model of the building. This approach differs from traditional way of creating architecture drawings in a static manner and introduces intelligence to the process of creating a digital design, enabling compliance evaluation to happen along with the design process.

The technical mechanism to enable the interactions between the autonomous AI agents and the semantic BIM databases is the heart of this ecosystem. These agents are not capable of geometric query but using a rich object-oriented repository, the geometric query with the standardized open data formats (e.g., Industry Foundation Classes (IFC)) is carried out (Ghannad et al., 2019). They rely on fine-grained metadata, such as material specifications, spatial adjacencies, structural hierarchies and other design elements, retrieved from specific application programming interfaces (APIs) developed by specialists to match them with the relevant parts of the regulations and to understand them contextually in the operation environment of the agents.

Based on this structural interaction, the framework proposes three general theoretical statements as guidelines for future empirical studies and future system designs. The first is the legal information and text conversion to structured, machine-readable semantic rules, for which Natural Language Processing (NLP) could be used successfully. Clauses, conditional restrictions, and jurisdictional exceptions can be systematically extracted (Guo et al., 2021). from human language in a legal text and converted to executable logical predicates as the foundation for automatic assessments of compliance (Zheng et al., 2022).

Table 1: Comparative Matrix of Compliance Paradigms

Compliance Paradigm	Speed	Adaptability	Cost
Traditional Manual Review	**Slow** (Weeks to months) Subject to human bottlenecks and backlogs.	**High** (Human judgment) Easily adapts to ambiguous rules, nuances, and context.	**High** (Labor-intensive) Requires large teams of experts and repeated billable hours.
First-Generation Rule-Based BIM	**Moderate** (Hours to days) Automates geometric checks but struggles with complex queries.	**Low** (Rigid algorithms) Breaks down when faced with non-standard designs or subjective codes.	**Moderate** (Upfront investment) High initial software and setup costs, with lower ongoing labor.
AI-Enabled Dynamic Compliance	**Real-time / Instantaneous** (Seconds to minutes) Processes massive datasets and models concurrently.	**Very High** (Continuous learning) Adapts dynamically to code updates, localized variances, and edge cases.	**Optimized / Scalable** (Lower long-term) High initial R&D replaced by massive efficiency gains and risk reduction.

Comparative Matrix of Compliance Paradigms (Ismail *et al*., 2023)

The second main claim is about diagnostic accuracy: that machine learning algorithms greatly diminish false-positive clashes and compliance errors compared to traditional static rule engines (Hu & Castro-Lacouture, 2019). Many of these automated rule-checking systems are based on classical approaches which may lead to false non-conformities due to the rigorous nature of the geometric tolerances involved and the lack of support from the classical systems to spatial intent or contextual exception rules. The proposed framework can be used to learn from past architectural corrections, including the capacity to differentiate between actual risk issues and acceptable design variations (Bloch & Sacks, 2020), which can be performed using probabilistic machine learning models and pattern recognition utilizing computer vision techniques.

The third proposition is about operational agility, where the time between the AI inference model and architectural design software can be shortened by real-time feedback loops to reduce the iteration cycle time. Compliance checking is currently performed reactively and at a number of major milestone design reviews, as well as at the end of design, resulting in costly design iterations. There is also continuous background auditing, where AI agents can automatically detect non-compliant changes in the modeling space and provide real-time visual alerts and remediation recommendations to architects (Sydora & Stroulia, 2020).

Last, the framework proposed in this paper unifies agent-driven interaction, semantic data structures and cognitive intelligence into one theoretical framework. These mechanisms can be codified in explicit propositions concerning the natural language translations, error reductions and real-time feedback and provide a strong foundation for architectural conformance in the next generation. This conceptual blueprint is designed to help resolve current technological challenges, as well as to establish the foundations for adaptive and self-governing architectural design ecosystems.

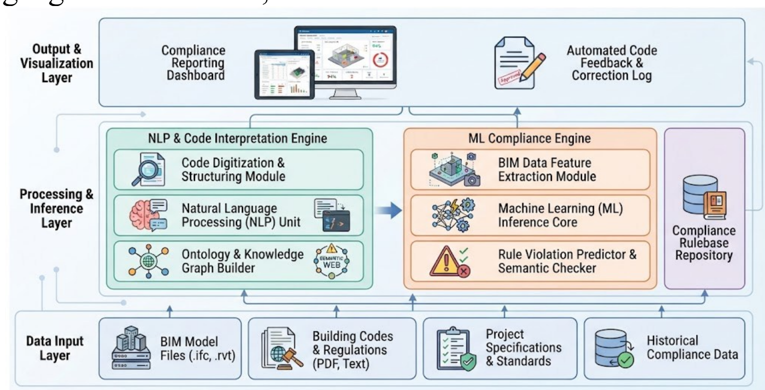

Fig. 2: AI-Enabled BIM Compliance System Architecture (Peng & Liu, 2023)

4.0 Regulatory Complexity and AI Capability Mapping

Architectural compliance territory is a place of complexities and variations. Building codes are formulated in many different ways, have different legal intentions, and are assessed using different criteria (Beach *et al.,* 2020; Nawari, 2019). Not all building regulations are equal: some lay down absolute physical dimensions and types of materials, other building regulations prescribe general functional requirements for designers to meet (Amor & Dimyadi, 2021). Therefore, regulatory complexity must be correlated with AI capabilities to build strong and flexible compliance verification systems (Sacks *et al.,* 2020). This section delves into the structural duality of building codes and assesses the different levels of AI maturity to meet different levels of regulatory oversight (Pan & Zhang, 2021).

Prescriptive codes are the simplest domain in which automated verification is possible within regulatory frameworks, because they are based on explicit, deterministic parameters (Ghannad *et al.,* 2019). Prescriptive codes specify definite numerical values, such as a required 1,500-millimetre (mm) corridor width, a certain distance to be travelled to a fire exit or a particular Fire Resistance (FR) level for steel columns (Kodur *et al.,* 2019). These requirements are absolute and binary and thus are very well suited for traditional rule-based engines and early automated checking tools (Xu & Cai, 2021). Prescriptive compliance can be evaluated by simple relational, geometric, and numerical queries over BIM databases that result in high degrees of computational confidence and little interpretive ambiguity (Bloch & Sacks, 2020).

On the contrary, more and more modern architectural practice is moving in the direction of performance-based codes that concentrate on the desired results of the building, not physical prescriptions (Van Coile *et al.,* 2019). Performance-based requirements specify a qualitative safety requirement, environmental requirement, or structural requirement, such as safe occupant evacuation under complex smoke dispersion conditions or optimization of the thermal comfort of the occupants inside without detailing the use of materials (Lovreglio *et al.,* 2020). These codes demand extensive contextual analysis, multi-variable trade-off analysis, and knowledge of the phenomena of physical simulation (Naser, 2021). In this area, traditional rule engines are hopeless, unable to interpret open-ended qualitative intent, exceptional conditions in context, or dynamically changing spatial performance metrics (Zheng *et al.,* 2022).

The architectural technology ecosystem needs to harmoniously resonate between AI maturity and regulatory depth to meet the demands of performance-based standards (Abioye *et al.,* 2021). Inherent constraints of early generations of digital checkers and static logic models are that they can only execute deterministic rules, so it is not possible to parse any subjective or ambiguous safety parameters (Zhou *et al.,* 2022). To overcome this capability gap, progress towards cognitive AI architectures with multi-layered reasoning, probabilistic inference, and advanced semantic understanding is needed (Baduge *et al.,* 2022). When matched with the proper level of AI, the building regulation serves as a proper layer of AI to prevent system failure and to make it possible to use automated tools in the real world for design intricacies (Wu *et al.,* 2022).

Ambiguous spatial and safety requirements are supported by the 'cognitive mechanics' of advanced deep learning models, knowledge graphs and neural-symbolic integration (Garcez & Lamb, 2023; Sarker *et al.,* 2021). Deep learning systems can assess intricate spatial arrangements based on abstract safety standards, by analysing historical building designs, simulation outputs of structures, and expert engineering annotations (Hodges *et al.,* 2019; Zhang *et al.,* 2022). Moreover, computer vision and geometric deep learning allow models to understand complex spatial relationships between elements of 3D BIM that go beyond mere numerical boundaries and enable the system to intelligently reason about complex egress behaviors, accessibility flows, emergency structural resilience, and more (Koo *et al.,* 2021; Wang *et al.,* 2022).

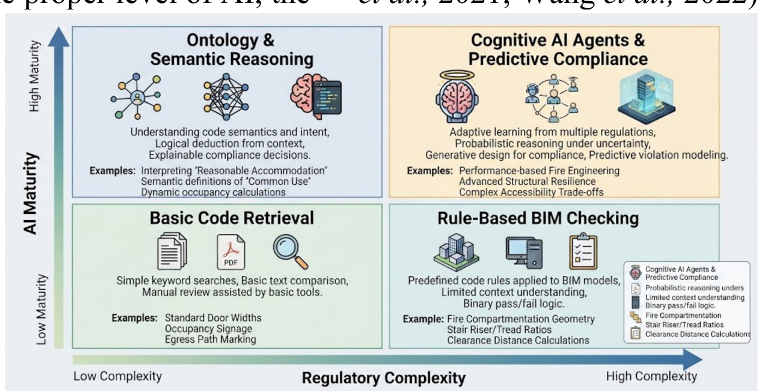

Fig. 3: Regulatory Complexity vs. AI Maturity Graph (Zhang & El-Gohary, 2022)

5.0 Challenges, Barriers, and Ethical Considerations

Building regulations can be categorised and mapped to the AI maturity levels and thus be structured in a systematic way for intelligent compliance-checking purposes (Nawari, 2019). It conveys the notion that there does not exist a common algorithmic procedure to achieve automation in architecture and that a hybrid architecture that implements deterministic rule engines for prescriptive checks and cognitive machine learning agents for performance-based checks is needed (Zhang & El-Gohary, 2021). This alignment makes sure that the conceptual framework is used to seamlessly connect to rigorous statutory requirements and advanced digital design workflows (Xue & Zhang, 2021).

The technical, legal and operational challenges involved in the transition from conceptual BIM compliance using AI to industry-wide actualization is a complex matrix (Darko et al., 2020). While the benefits of cognitive computing and automated rule engines can deliver unprecedented efficiencies, there are structural challenges and embedded industry practices encountered in the Architecture, Engineering, and Construction (AEC) industry (Delgado et al., 2019). The solutions to these problems will be essential to ensuring the reliability of the system and the development of trust for autonomous governance models on the part of stakeholders (Glikson & Woolley, 2020).

One of the most immediate technical issues is still data interoperability, which is affected by proprietary software formats and procedures that belong to the vendors (Ozturk, 2020). Spatial data and semantic attributes are often represented in non-standardized, diverse, and closed-ecosystems modeling platforms that are widely used by architectural design offices (Shirowzhan *et al.,* 2020). These diverse documents often have structural discrepancies and information loss when trying to be automatically read by compliance agents, which compromises the integrity of evaluation (Wu & Zhang, 2019; Zhu *et al.,* 2019). To realize seamless AI integration, there needs to be a decisive industry-wide shift towards open standards and data democratization (Turk, 2020).

The Industry Foundation Classes (IFC) are the main technical solution to these interoperability "bottlenecks" (even if the fidelity of the data is still a challenge) (Jiang *et al.,* 2019). IFC offers a neutral schema for transferring BIM data, but its inconsistencies are prone to corrupt object hierarchies or losing material properties when implemented across different software vendors (Noardo *et al.,* 2021). To make AI-powered compliance systems effective, consistent extensions and strict schema validity rules need to be in place so that the cognitive agents can tap into clean, uncontroversial semantic information, unaffected by the authoring software employed (Kincelova *et al.,* 2020).

In addition to the technical interoperability issues, integration of autonomous compliance systems poses fundamental issues of legal responsibility and professional liability (Nawari & Ravindran, 2019). In the past, it was the licensed architect of record who was solely responsible for making sure a building design met local code, zoning and safety requirements (Li *et al.,* 2019). The introduction of AI validation layers introduces these blurred lines of responsibility, leading to complicated legal issues if an AI-validated BIM model does not meet physical inspections or if there are structural failures on site (Mökander *et al.,* 2021). The need for new legislation that clarifies who is liable when companies use AI software is an immediate necessity for commercial rollout, involving software vendors, AI developers, and human practitioners (Buiten, 2019; Smuha, 2021).

Compliance systems need to address the "black box" challenge and incorporate the use of Explainable AI (XAI) to alleviate legal fears and professional opposition (Arrieta *et al.,* 2020; Rudin, 2019). Architects shouldn't be asked to change big design decisions, based on black-and-white results they've been receiving from hard-to-explain machine learning algorithms (Shin, 2021). Explainable AI architectures deliver clear, explainable rationales for each compliance assessment, clearly stating which geometric parameters, spatial requirements or regulatory clauses caused a flag (Samek *et al.,* 2021). This transparency allows the architect to gain insight into the rationale of the system, check its correctness, and be creative in adapting the system into the design (Miller, 2019).

Finally, these challenges are multifaceted and should be tackled jointly and multidisciplinarily, including aspects of the architectural practice as well as software engineering and legal jurisprudence (Regona et al., 2022). For the industry, it is important to use automation safely, which can be done by solving the data interoperability problems by utilizing universal open standards, establishing transparent liability mechanisms and incorporating Explainable AI (XAI) into the verification process (Mökander et al., 2021). Solutions to address these challenges involve evolving AI-compliance tools into a more collaborative and reliable partner, enhancing the quality and standards of architectural design and management (Glikson & Woolley, 2020).

Table 2: Risk and Mitigation Matrix

Risk Category	Identified Risk	Potential Impact	Proposed Mitigation Strategy
Technical	Model Hallucination / False Positives: AI misinterprets complex building codes or spatial geometry.	High: Approving non-compliant designs, leading to structural failures or costly redesigns.	Implement a human-in-the-loop (HITL) validation framework for critical life-safety checks and continuously benchmark AI outputs against ground-truth datasets.
Legal	Liability Ambiguity: Unclear accountability when an AI-cleared design violates statutory regulations.	Critical: Severe legal liabilities, lawsuits, and loss of professional licensing for firms.	Establish clear contractual disclaimers, maintain comprehensive audit trails of AI decisions, and require certified professional sign-off for all final submittals.
Operational	Data Silos and Legacy Format Incompatibility: Difficulty integrating AI pipelines with proprietary or outdated CAD/BIM tools.	Moderate: Workflow friction, integration delays, and fragmented team adoption.	Adopt open standards (e.g., IFC – Industry Foundation Classes) and build modular API layers to bridge legacy systems with modern cloud-based AI engines.

Risk and Mitigation Matrix **(Villaschi, Carvalho & Bragança, 2022)**

6.0 Conclusion

In this conceptual paper, principles and goals have been defined related to legacy, static rule checking systems and towards cognitive and AI driven Building Information Modeling (BIM) compliance ecosystems. The synergy of combining architectural technology, natural language processing and semantic data structures is systematically analyzed and investigated in the study and the study is used to investigate agility of intelligent agents to interpret complex regulatory frameworks. The proposed framework not only seeks to reconcile the self-evident limitations of the traditional prescriptive codes and the fluidity of the performance codes – an effort to overcome the difficulty of applying computation to automate a process, while maintaining professional practice of architecture; but also seeks to balance the rigidity of the traditional prescriptive codes and the fluidity of the performance codes.

Therefore, there is a strong need for a high-quality research program in the future based upon these theoretical assertions, that is designed to test, validate and improve the proposed compliance architecture through empirical research. The first step towards this roadmap should be to create the full software prototypes which enable full integration of the open Industry Foundation Classes (IFC) data schemas and to support a transformer-based NLP pipeline. Through multi-storey architectural datasets, scientists will perform controlled simulation tests that will allow them to assess the ability of the system to provide accurate identification of conflicting architectural rules, false positive clash detection and real-time feedback into working modeling environments.

A step from stand alone simulation in the laboratory to real pilot projects conducted by practicing architects and at the level of regulatory authorities is desirable in future empirical research. Moreover, case studies will be important for quantifying how well users trust AI systems and the success of Explainable AI (XAI) interfaces, and to design and manage complex legal issues surrounding AI validation failures. Finally, this huge research program will contribute to developing a system of homogeneous and autonomous architectural technologies which will ease the project life cycle and ensure the greatest safety and compliance standards.

6.0 References

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Delgado, J. M. D., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering*, 44, 103299. https://doi.org/10.1016/j.jobe.2021.103 299

Amor, R., & Dimyadi, J. (2021). The promise of automated compliance checking. *Developments in the Built Environment*, 5, 100039, https://doi.org/10.1016/j.dibe .2020.100039

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, 58, pp. 82–115.

Aydın, M., & Yaman, H. (2020). A literature review of automated code compliance checking concept. *Journal of Design+Theory*, 16, 29, pp. 79–97.

Aydın, M., & Yaman, H. (2020). Domain knowledge representation languages and methods for building regulations. In S. Ofluoglu, U. Isikdag, & O. O. Ozener (Eds.), *Advances in Building Information Modeling: 1st Eurasian BIM Forum, EBF 2019* (pp. 101–121). Springer.

Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A., & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, 141, 104440,https://doi.org/10.1016/j.autcon.20 22.104 440.

Beach, T. H., Hippolyte, J.-L., & Rezgui, Y. (2020). Towards the adoption of automated regulatory compliance checking in the built environment. *Automation in Construction*, 118, 103285, https://doi.org/10.1016/ j.autcon.2020.103285.

Bloch, T., & Sacks, R. (2020). Clustering information types for semantic enrichment of building information models to support automated code compliance checking. *Journal of Computing in Civil Engineering*, 34, 6, 04020040, https://doi.org/10.1016/j. autcon.2020.103285

Buiten, M. C. (2019). Towards intelligent regulation of artificial intelligence. *European Journal of Risk Regulation*, 10, 1, pp. 41–59.

Darko, A., Chan, A. P. C., Adabre, M. A., Edwards, D. J., Hosseini, M. R., & Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Automation in Construction*, 112, 103081, https://doi.org/ 10.1016/j.autcon.2020.103081.

Delgado, J. M. D., Oyedele, L., Ajayi, A., Akanbi, L., Akinade, O., Bilal, M., & Owolabi, H. (2019). Robotics and automated systems in construction: Understanding industry-specific challenges for adoption. *Journal of Building Engineering*, 26, 100868, https://doi.org/10.1016/j.autcon.2020.103081.

Deng, M., Menassa, C. C., & Kamat, V. R. (2021). From BIM to digital twins: A systematic review of the evolution of intelligent building representations in the AEC-FM industry. *Journal of Information Technology in Construction*, 26, pp. 58–83.

Ding, Y., Ma, J., & Luo, X. (2022). Applications of natural language processing in construction. *Automation in Construction*, 136, 104169, https://doi.org/10.1016/j.autcon.2022.104169

Ekanayake, B., Wong, J. K.-W., Fini, A. A. F., & Smith, P. (2021). Computer vision-based interior construction progress monitoring: A literature review and future research directions. *Automation in Construction*, 127, 103705, https://doi.org/10.1016/j.autcon.2021.103705.

Fan, S.-L., Chi, H.-L., & Pan, P.-Q. (2019). Rule checking interface development between building information model and end user. *Automation in Construction*, 105, 102842.https://doi.org/10.1016/j.autcon.2019.102842

Fang, W., Ma, L., Love, P. E. D., Luo, H., Ding, L., & Zhou, A. (2020). Knowledge graph for identifying hazards on construction sites: Integrating computer vision with ontology. *Automation in Construction*, 119, 103310, https://doi.org/10.1016/j.autcon.2020.103310.

Garcez, A. D., & Lamb, L. C. (2023). Neurosymbolic AI: The 3rd wave. *Artificial Intelligence Review*, 56, 11, pp. 12387–12406.

Ghannad, P., Lee, Y.-C., Dimyadi, J., & Solihin, W. (2019). Automated BIM data validation integrating open-standard schema with visual programming language. *Advanced Engineering Informatics*, 40, pp. 14–28.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14, 2, pp. 627–660.

Guo, D., Onstein, E., & La Rosa, A. D. (2021). A semantic approach for automated rule compliance checking in construction industry. *IEEE Access*, 9, pp. 129648–129661.

Hodges, J. L., Lattimer, B. Y., & Luxbacher, K. D. (2019). Compartment fire predictions using transpose convolutional neural networks. *Fire Safety Journal*, 108, 102854, https://doi.org/10.1016/j.autcon.2020.103310.

Hu, Y., & Castro-Lacouture, D. (2019). Clash relevance prediction based on machine learning. *Journal of Computing in Civil Engineering*, 33, 2, 04018060, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000810

Hu, Y., Xia, C., Chen, J., & Gao, X. (2023). Clash context representation and change component prediction based on graph convolutional network in MEP disciplines. *Advanced Engineering Informatics*, 55, 101896, https://doi.org/10.1016/j.autcon.2021.103705.

Ismail, A. S., Ali, K. N., Iahad, N. A., Kassem, M. A., & Al-Ashwal, N. T. (2023). BIM-based automated code compliance checking system in Malaysian fire safety regulations: A user-friendly approach. *Buildings*, 13, 6, 1404. https://doi.org/10.3390/buildings13061404

Jiang, S., Jiang, L., Han, Y., Wu, Z., & Wang, N. (2019). OpenBIM: An enabling solution for information interoperability. *Applied Sciences*, 9, 24, 5358, https://doi.org/10.3390/app9245358

Kincelova, K., Boton, C., Blanchet, P., & Dagenais, C. (2020). Fire safety in tall timber building: A BIM-based automated code-checking approach. *Buildings*, 10, 7, 121, https://doi.org/10.3390/buildings10070121

Kodur, V., Kumar, P., & Rafi, M. M. (2019). Fire hazard in buildings: Review, assessment and strategies for improving fire safety. *PSU Research Review*, 3, 1, pp. 1–23.

Koo, B., Jung, R., & Yu, Y. (2021). Automatic classification of wall and door BIM element subtypes using 3D geometric deep neural networks. *Advanced Engineering Informatics*, 47, 101200, https://doi.org/10.1016/j.aei.2020.101200.

Lee, Y.-C., Eastman, C. M., & Solihin, W. (2021). Rules and validation processes for interoperable BIM data exchange. *Journal of Computational Design and Engineering*, 8, 1, pp. 97–114.

Li, J., Greenwood, D., & Kassem, M. (2019). Blockchain in the built environment and construction industry: A systematic review, conceptual models and practical use cases. *Automation in Construction*, 102, pp. 288–307.

Love, P. E. D., Fang, W., Matthews, J., Porter, S. R., Luo, H., & Ding, L. (2023). Explainable artificial intelligence (XAI): Precepts, models, and opportunities for research in construction. *Advanced Engineering Informatics*, 57, 102024.

Lovreglio, R., Ronchi, E., & Kinsey, M. J. (2020). An online survey of pedestrian evacuation model usage and users. *Fire Technology*, 56, pp. 1133–1153.

Miller, T. (2019). Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267, pp. 1–38.

Mökander, J., Morley, J., Taddeo, M., & Floridi, L. (2021). Ethics-based auditing of automated decision-making systems: Nature, scope, and limitations. *Science and Engineering Ethics*, 27, 44, https://doi.org/10.1007/s11948-021-00319-4

Naser, M. Z. (2021). Mechanistically informed machine learning and artificial intelligence in fire engineering and sciences. *Fire Technology*, 57, pp. 2741–2784.

Nawari, N. O. (2019). A generalized adaptive framework (GAF) for automating code compliance checking. *Buildings*, 9, 4, 86.

Nawari, N. O., & Ravindran, S. (2019). Blockchain and the built environment: Potentials and limitations. *Journal of Building Engineering*, 25, 100832, https://doi.org/10.1016/j.jobe.2019.100832

Noardo, F., Krijnen, T., Arroyo Ohori, K., Biljecki, F., Ellul, C., Harrie, L., Eriksson, H., Polia, L., Salheb, N., Tauscher, H., van Liempt, J., Goerne, H., Hintz, D., Kaiser, T., Leoni, C., Warchol, A., & Stoter, J. (2021). Reference study of IFC software support: The GeoBIM benchmark 2019—Part I. *Transactions in GIS*, 25, 2, pp. 805–841.

Ozturk, G. B. (2020). Interoperability in building information modeling for AECO/FM industry. *Automation in Construction*, 113, 103122, https://doi.org/10.1016/j.autcon.2020.103122.

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, 122, 103517, https://doi.org/10.1016/j.autcon.2020.103517.

Peng, J., & Liu, X. (2023). Automated code compliance checking research based on BIM and knowledge graph. *Scientific Reports*, 13, 7065. https://doi.org/10.1038/s41598-023-34342-1

Regona, M., Yigitcanlar, T., Xia, B., & Li, R. Y. M. (2022). Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. *Journal of Open Innovation: Technology, Market, and*

Complexity, 8, 1, Article 45, https://doi.org/10.3390/joitmc8010045

Ren, R., & Zhang, J. (2021). A new framework to address BIM interoperability in the AEC domain from technical and process dimensions. *Advances in Civil Engineering*, 2021, Article 8824613, https://doi.org/10.1155/2021/8824613

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1, 5, pp. 206–215.

Sacks, R., Girolami, M., & Brilakis, I. (2020). Building information modelling, artificial intelligence and a construction tech. *Developments in the Built Environment*, 4, 100011, https://doi.org/10.1016/j.dibe.2020.100011

Samek, W., Montavon, G., Lapuschkin, S., Anders, C. J., & Müller, K.-R. (2021). Explaining deep neural networks and beyond: A review of methods and applications. *Proceedings of the IEEE*, 109, 3, pp. 247–278.

Sarker, M. K., Zhou, L., Eberhart, A., & Hitzler, P. (2021). Neuro-symbolic artificial intelligence: Current trends. *AI Communications*, 34, 3, pp. 197–209.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, 146, 102551, https://doi.org/10.1016/j.ijhcs.2020.102551.

Shirowzhan, S., Sepasgozar, S. M. E., Edwards, D. J., Li, H., & Wang, C. (2020). BIM compatibility and its differentiation with interoperability challenges as an innovation factor. *Automation in Construction*, 112, 103086, https://doi.org/10.1016/j.autcon.2020.103086.

Shrestha, S. (2021). Nature, nurture, or neither?: Liability for automated and autonomous artificial intelligence torts based on human design and influences. *George Mason Law Review*, 29, 2, pp. 375–410.

Smuha, N. A. (2021). From a "race to AI" to a "race to AI regulation": Regulatory competition for artificial intelligence. *Law, Innovation and Technology*, 13, 1, pp. 57–84, https://doi.org/10.1080/17579961.2021.1898300

Solihin, W., Dimyadi, J., Lee, Y.-C., Eastman, C., & Amor, R. (2020). Simplified schema queries for supporting BIM-based rule-checking applications. *Automation in Construction*, 117, 103248, https://doi.org/10.1016/j.autcon.2020.103248.

Sydora, C., & Stroulia, E. (2020). Rule-based compliance checking and generative design for building interiors using BIM. *Automation in Construction*, 120, 103368, https://doi.org/10.1016/j.autcon.2020.103368.

Turk, Ž. (2020). Interoperability in construction: Mission impossible? *Developments in the Built Environment*, 4, 100018, https://doi.org/10.1016/j.dibe.2020.100018

Van Coile, R., Hopkin, D., Lange, D., Jomaas, G., & Bisby, L. (2019). The need for hierarchies of acceptance criteria for probabilistic risk assessments in fire engineering. *Fire Technology*, 55, pp. 1111–1146.

Villaschi, F. S., Carvalho, J. P., & Bragança, L. (2022). BIM-based method for the verification of building code compliance. *Applied System Innovation*, 5, 4, 64. https://doi.org/10.3390/asi5040064

Wang, N., Issa, R. R. A., & Anumba, C. J. (2022). NLP-based query-answering system for information extraction from building information models. *Journal of Computing in Civil Engineering*, 36, 3, 04022004, https://doi.org/10.1061/(ASCE)CP.1943-5487.0001019

Wang, Z., Sacks, R., & Yeung, T. (2022). Exploring graph neural networks for semantic enrichment: Room type classification. *Automation in Construction*, 134, 104039, https://doi.org/10.1016/j.autcon.2021.104039.

Wu, C., Li, X., Guo, Y., Wang, J., Ren, Z., Wang, M., & Yang, Z. (2022). Natural language processing for smart construction: Current status and future directions. *Automation in Construction*, 134, 104059, https://doi.org/10.1016/j.autcon.2021.104059.

Wu, C., Wu, P., Wang, J., Jiang, R., Chen, M., & Wang, X. (2021). Developing a hybrid approach to extract constraints related information for constraint management. *Automation in Construction*, 124, 103563, https://doi.org/10.1016/j.autcon.2021.103563.

Wu, J., & Zhang, J. (2019). New automated BIM object classification method to support BIM interoperability. *Journal of Computing in Civil Engineering*, 33, 5, 04019033, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000858

Xu, X., & Cai, H. (2021). Ontology and rule-based natural language processing approach for interpreting textual regulations on underground utility infrastructure. *Advanced Engineering Informatics*, 48, 101288, https://doi.org/10.1016/j.aei.2021.101288.

Xue, X., & Zhang, J. (2021). Part-of-speech tagging of building codes empowered by deep learning and transformational rules. *Advanced Engineering Informatics*, 47, 101235, https://doi.org/10.1016/j.aei.2020.101235.

Yang, A., Han, M., Zeng, Q., & Sun, Y. (2021). Adopting building information modeling (BIM) for the development of smart buildings: A review of enabling applications and challenges. *Advances in Civil Engineering*, 2021, Article 8811476, https://doi.org/10.1155/2021/8811476

Zhang, R., & El-Gohary, N. (2021). A deep neural network-based method for deep information extraction using transfer learning strategies to support automated compliance checking. *Automation in Construction*, 132, 103834, https://doi.org/10.1016/j.autcon.2021.103834.

Zhang, R., & El-Gohary, N. (2022). Building information modeling, natural language processing, and artificial intelligence for automated compliance checking. In *Research Companion to Building Information Modeling*. Edward Elgar Publishing. https://doi.org/10.4337/9781839105524.00022

Zhang, R., & El-Gohary, N. (2022). Natural language generation and deep learning for intelligent building codes. *Advanced Engineering Informatics*, 52, 101557. https://doi.org/10.1016/j.aei.2022.101557

Zhang, T., Wang, Z., Wong, H. Y., Tam, W. C., Huang, X., & Xiao, F. (2022). Real-time forecast of compartment fire and flashover based on deep learning. *Fire Safety Journal*, 130, 103579, https://doi.org/10.1016/j.firesaf.2022.103579

Zheng, Z., Lu, X.-Z., Chen, K.-Y., Zhou, Y.-C., & Lin, J.-R. (2022). Pretrained domain-specific language model for natural language processing tasks in the AEC domain. *Computers in Industry*, 142, 103733, https://doi.org/10.1016/j.compind.2022.103733.

Zheng, Z., Zhou, Y.-C., Lu, X.-Z., & Lin, J.-R. (2022). Knowledge-informed semantic alignment and rule interpretation for automated compliance checking. *Automation in Construction*, 142, 104524, https://doi.org/10.1016/j.autcon.2022.104524.

Zhong, B., Xing, X., Luo, H., Zhou, Q., Li, H., Rose, T., & Fang, W. (2020). Deep learning-based extraction of construction procedural constraints from construction regulations. *Advanced Engineering*

Informatics, 43, 101003, https://doi.org/10.1016/j.aei.2019.101003.

Zhou, Y., Zheng, Z., Lin, J.-R., & Lu, X.-Z. (2022). Integrating NLP and context-free grammar for complex rule interpretation towards automated compliance checking. *Computers in Industry*, 142, 103746, https://doi.org/10.1016/j.compind.2022.103746.

Zhu, J., Wang, X., Chen, M., Wu, P., & Kim, M. J. (2019). Integration of BIM and GIS: IFC geometry transformation to shapefile using enhanced open-source approach. *Automation in Construction*, 106, 102859, https://doi.org/10.1016/j.autcon.2019.102859.

Compliance with Ethical Standards

Declarations:

The authors declare that they have no conflict of interest.

Data availability

All data used in this study will be readily available to the public.

Consent for publication

Not Applicable.

Ethical Consideration

This has been declared in Section 3 of the text

Availability of data and materials: The publisher has the right to make the data public.

Competing interests

The authors declared no conflict of interest.

Funding

The authors declared no source of funding

Authors' Contributions

The author carried out all components of the work