Research on the Structure and Transmission of Enhanced IFC for LLM-Driven Intelligent Design

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Abstract

With the growing use of artificial intelligence in architectural design, BIM models now need to record not only geometric shapes but also process information and external knowledge for intelligent design and optimization. This paper introduces an enhanced semantic IFC (Industry Foundation Classes) model to transmit process and semantic data during design. By aligning large-scale model data and leveraging RAG for intelligent design, we extend the IFC standard to support multi-stage design exchanges. Additionally, blockchain and AES encryption are integrated into the IFC model to address copyright and security concerns, enabling traceable verification and encrypted storage. This approach improves the intelligence, security, and integrity of architectural design data, offering new directions for the future of information modeling technologies.

Keywords –

Intelligent Design; LLM; Blockchain; Enhanced Semantic; IFC

1 Introduction

Building Information Modeling (BIM) is the cornerstone of digital transformation in architecture, enhancing management accuracy and cross-stage interoperability [1, 5]. Recently, Generative AI and Large Language Models (LLMs) have shifted the design paradigm from manual exploration to human-machine collaboration, offering exceptional capabilities in conceptual generation and parameter recommendation [2, 3]. However, while these intelligent workflows significantly boost efficiency, they introduce complex semantic contexts, reasoning chains, and implicit knowledge that are vital for downstream visualization and review [4].

Despite its maturity, the Industry Foundation Classes (IFC) standard exhibits significant deficiencies in capturing these AI-driven outputs. Existing IFC schemas excel at encoding geometry but struggle to represent design intent, knowledge associations, and the generative reasoning produced by LLMs [6]. This results in semantic fragmentation within BIM-integrated workflows. Current academic efforts—primarily focused on RDF/OWL-based lightweight annotations—lack a comprehensive mechanism to map the multi-dimensional semantic structures of generative models directly to the IFC framework [7].

To bridge this gap, this study integrates Knowledge Graph (KG) technology into the semantic enhancement of IFC [8]. KGs excel at modeling complex entity-relationship structures and support multi-hop reasoning, making them inherently compatible with the graph-based outputs of large models [9]. By leveraging the structured nature of KGs, this approach not only improves semantic retrieval and interoperability but also facilitates the construction of controlled, privacy-protected knowledge bases within industrial BIM practices [10].

Based on the above background and needs, this paper proposes an IFC semantic enhancement and encryption method driven by AI large-model generative design. The main contributions of this study are as follows: First, a systematic analysis of the semantic features of large-model generative design is conducted, identifying key elements in terms of semantic types, structured requirements, and visualization integration. Second, the IFC data schema is extended in a targeted manner, mapping knowledge graph representation mechanisms into IFC or its associated external files, thereby increasing semantic coverage while maintaining compatibility with BIM visualization software. Third, a corresponding encryption verification process is established based on smart contracts and encryption algorithms, ensuring the security of IFC design data during transmission and the adaptability of each design version.

Existing BIM semantic enrichment (e.g., ASK-BIM [11]) fully converts the BIM physical model into a Large-Scale Knowledge Graph (KG) for LLM-based query. However, this approach faces significant challenges in full-scale IFC conversion, token costs during reasoning, and computational redundancy. In contrast, our proposed SE-IFC architecture achieves critical breakthroughs, as summarized in Table 1.

Table 1. Comparison: ASK-BIM vs. SE-IFC

Item	ASK-BIM	Proposed SE-IFC	Advancement
Graph Strategy	Full-Scale conversion of all physical BIM data	Partial Mounting on-demand semantic enrichment	Token Efficiency & Scalability for LLM reasoning
Structure	Difficult to align BIM with external datasets	On-demand Mounting: Seamlessly links multi-layer external VLM data	High Scalability & Ease of implementation
Reasoning	Monolithic graph lacking versioning capabilities	Records reasoning chains and knowledge-base rules	Full Traceability of the design process

2 Intelligent Design Based on LLM

This study introduces an intelligent design paradigm leveraging the contextual reasoning of LLMs, rather than data-intensive deep learning. By utilizing few-shot prompting with exemplar-based learning, the system generates layouts via linguistic reasoning without manual annotation. To ensure controllability and interpretability, three mechanisms are implemented:

- semantic knowledge-base: Explicitly structures design codes and spatial logics as hard constraints.
- self-verification: Automatically inspects and corrects LLM outputs based on knowledge-base feedback.
- Cross-platform parametric generation: Translates structured instructions into 3D models via BIM APIs

This integrated pipeline—from linguistic reasoning to autonomous verification and parametric modeling—balances model flexibility with practical engineering deployability.

2.1 Preprocessing of Housing Layout Data

To support the LLM-based intelligent design, this study utilizes the 3D-FRONT dataset [12] as a source of high-quality spatial priors. Rather than traditional energy-intensive training, a subset of 980 bedroom and living room layouts is employed to construct a structured example library. Each layout, comprising components like tables, beds, and wardrobes (Figure 1), is preprocessed into a standardized format.

(a)Front view (b)Top view (c)Side view (d)Oblique view

Figure 1. Original indoor layout data

To support the LLM-based design process, 3D-FRONT layout data are preprocessed and standardized into a consistent format. Key geometric features—including room dimensions and object-level attributes (type, size, coordinates, and orientation)—are extracted and serialized into structured JSON. This machine-readable representation ensures that the LLM can efficiently parse both spatial and semantic information through few-shot prompting, facilitating high-fidelity layout generation without manual intervention. Table 2 illustrates the extracted parameters and their structured representation.

Table 2. JSON Schema for Indoor Layouts

Parameter Group	Description	Example
Spatial Envelope	Room type, length, width (m)	LivingRoom, 6.0, 5.0
Object Geometry	Type, L, W, H, Depth (m)	wardrobe, 2.2, 2.4, 1.1
Position	Left/top offsets (m), Orientation (°)	1.8, 1.4, 90°

2.2 Adaptive Knowledge Base and Agent Updates in RAG Framework

In intelligent design systems, especially for complex tasks such as residential layout planning, large language models (LLMs) can efficiently generate design solutions based on preloaded datasets. However, they often rely on fixed rules and historical data, which limits flexibility for iterative and interactive design. Traditional digitized floor-plan methods lack dynamic rule-update capabilities, constraining adaptive design processes. To overcome the rigidity and "black-box" nature of traditional LLMs, this study integrates an external Retrieval-Augmented Generation (RAG) knowledge base. This repository explicitly stores furniture specifications (e.g., 3D-FRONT dimensions), design codes (e.g., clearances), and accessibility constraints. By integrating these knowledge categories into the RAG framework, the system can adaptively update design rules, providing context-aware guidance that enhances flexibility, safety, and practicality in AI-generated layouts.

Taking residential layout design as an example, the overall process is illustrated in Figure 2. The system employs three functionally distinct agents to collaboratively complete the task. First, the Review agent performs knowledge-base matching and constraint validation on the initial design generated by the LLM, outputting any non-compliant elements in JSON format. Next, the Revision agent leverages these flagged items and invokes built-in operational functions (including move, rotate, and parameter adjustments) to revise and regenerate the layout. Finally, the Modeling agent converts the revised layout into parametric modeling instructions, achieving a complete pipeline from conceptual design generation to practical implementation.

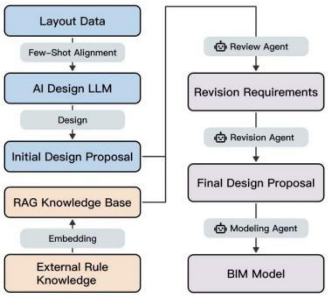

Figure 2. Full process of LLM-Driven intelligent design

2.3 Cross-Platform BIM Visualization

BIM Integration & MCP Execution. The transition from textual layout parameters to physical building components relies on a parametric component library built via BIM software APIs. These components function as a programmable "toolset," ensuring consistent data formats between LLM outputs and internal agents.

As shown in Figure 3, the workflow proceeds from parsing LLM drafts to invoking specific toolset functions. These functions are registered at the Model Context Protocol (MCP) layer and transmitted via TCP communication to a 3D modeling server for execution [13]. Each server-side function maintains a one-to-one mapping with its MCP counterpart, ensuring traceable execution and automated visual reconstruction within the BIM environment.

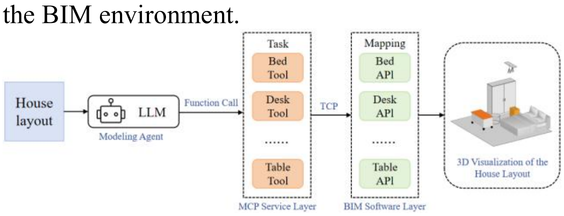

Figure 3. MCP-Based parametric component visualization in BIM

3 Semantic Enhancement of IFC for LLM-Based Design

In traditional BIM workflows, data interoperability across different software platforms typically relies on the IFC format, which separates geometric information from semantic attributes, ensuring a stable and extensible information structure.However, for the semantic-driven, large-model – based design paradigm proposed in this study, the native IFC schema is no longer sufficient to capture the full spectrum of design intent, reasoning logic, semantic constraints, and generative context produced by large language models. To address this limitation, we introduce a semantic extension to the traditional IFC format, upgrading it from a geometry-centric exchange standard to a Semantic-Enhanced IFC capable of representing design knowledge, generative context, and the underlying reasoning chain produced during intelligent layout generation.

This study expands the semantic hierarchy of IFC geometry files using the open-source IFCOpenShell library. The enhanced IFC retains the standard spatial organization structure IFCPROJECT → IFCSITE → IFCBUILDING → IFCBUILDINGSTOREY—thereby ensuring full compatibility with mainstream BIM authoring tools.

On this foundation, we introduce two additional semantic carriers: a Display Modification Layer and a Hidden Semantic Layer. These extensions enrich the IFC with design-generation semantics while preserving its original geometric and attribute structure. The overall framework is illustrated in Figure 4, where the blue region represents native IFC content and the pink region denotes the newly added semantic enhancements.

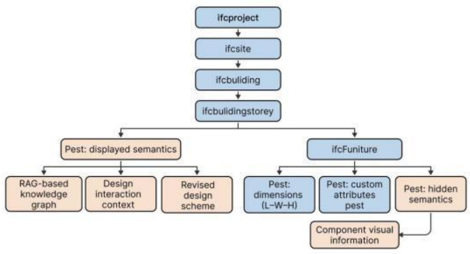

Figure 4. Structural schema of the semantic-enhanced IFC

Display Semantic Layer. Integrated at the IFCBUILDINGSTOREY level, this layer functions as a global annotation container for cross-component design logic. It archives three core elements:

1. **Agent Execution Logs**：Records intelligent agent

types and tool functions (e.g., AgentFunctionCall, ToolName, Timestamp) to ensure full traceability of the generation-validation-optimization chain.

2. **Retrieved RAG Knowledge and Associated Constraint Rules：** Embeds external knowledge retrieved during iterations — such as furniture specifications, safety clearances, and circulation rules — preserving a transparent record of the normative logic guiding design adjustments.
3. **Modification Localization and Interaction Context:** Tracks semantic localization of modifications by logging natural-language prompts and agent rationales. This multimodal documentation transforms the IFC from a static geometry container into an interaction-aware semantic entity.

Through this enriched recording mechanism, the IFC model evolves from a static geometric container into an interpretable, interaction-aware semantic entity.

At the IFCFURNITURE level, an additional Hidden Semantic Layer is introduced to capture deep semantic features that extend beyond the explicit information stored in the display layer. This layer records latent visual and structural attributes that emerge during the later stages of intelligent layout generation, including furniture color composition, material textures, fine-grained structural details, and other non-essential micro-parameters.these types of features are typically difficult to extract directly through conventional parametric design workflows, as their complete representation often depends on the APIs provided by third-party modeling software. However, most commercial BIM platforms expose only limited geometry or attribute parameters, resulting in missing information related to visual details and semantic completeness.

To address this limitation, this study incorporates a Vision-Language Model (VLM) – based semantic enhancement mechanism. Leveraging the visual encoding capabilities of VLMs, the system extracts implicit feature representations of furniture objects directly from rendered images. This enables multimodal alignment between images and textual descriptors, allowing implicit semantic modeling of appearance attributes, material characteristics, and spatial composition relationships—without requiring access to low-level geometric APIs.

Ultimately, the Hidden Semantic Layer serves as a complementary semantic container within the IFC hierarchy. While the display semantic layer focuses on explicit interaction logs and design revisions, the hidden layer concentrates on reconstructing and enriching implicit visual semantics. Together, these two layers establish a dual-semantic structure for the enhanced IFC model, enabling IFC files to describe not only parametric geometric properties but also deep semantic information derived from large-model reasoning. This results in an interpretable and evolvable information representation framework tailored for intelligent design systems.The specific augmented IFC schema is illustrated in Figure 5.

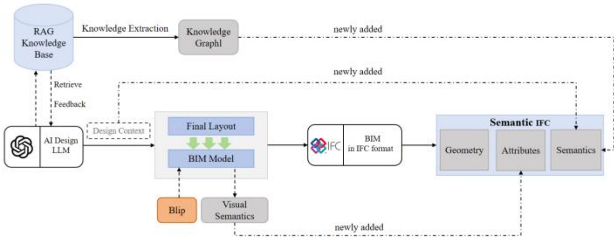

Figure 5. Flowchart of the semantic-enhanced IFC implementation process

Overall, this framework provides a robust foundation for semantic BIM modeling and intelligent reasoning, enabling secure, scalable, and interoperable knowledge integration within intelligent design systems.

4 Blockchain- and AES-Based Secure Management of IFC Files

This paper proposes an innovative IFC information security method that combines blockchain verification with AES encryption to address data integrity and privacy concerns during multi-party collaboration. Rather than conventional full-file encryption or on-chain storage—which introduces prohibitive overhead for large BIM models — our approach employs a selective, layered security architecture that decouples geometric accessibility from semantic confidentiality.

The security framework operates through three distinct layers with strict separation of concerns:

Layer 1: Geometric Data (Off-Chain, Unencrypted)

IFC geometric entities remain in standard cleartext format,Stored via conventional BIM repositories.

Layer 2: Semantic Knowledge (Off-Chain, Encrypted)

Knowledge Graph triples (design intent, reasoning chains, constraint rules) serialized to JSON,AES-256-GCM encryption applied to JSON payload, producing compact ciphertext,Result: Semantic data remains confidential even if IFC file is exfiltrated.

Layer 3: Integrity Verification (On-Chain)

SHA-256 hash of (JSON KG + encryption) anchored to private Ethereum testnet,Only the hash resides on-chain; no geometric data, no semantic content, no IFC file fragments,the complete transmission process follows this Figure 6:

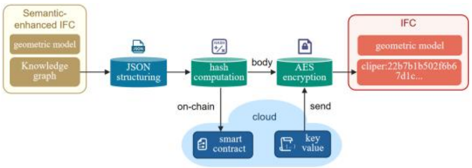

Figure 6. Semantic Encryption Workflow

4.1 The introduction of blockchain technology

In intelligent design applications, ensuring the uniqueness, immutability, and transparency of knowledge graphs is one of the key challenges. Blockchain technology, with its decentralized, tamper-proof, and highly transparent characteristics, provides a feasible technical solution to address these issues. By submitting the JSON sequence of the knowledge graph to the blockchain for smart contract management, each knowledge graph can be effectively recorded, ensuring the reliability and security of its data. The advantages of this approach over traditional IFC-based storage are illustrated in Table 3.

Table 3. Blockchain vs. Traditional IFC Storage

Feature	Traditional IFC Storage	Blockchain Technology
Data Integrity	Lacks immutability	Unique Hash
Traceability	Incomplete/Manual	Interaction-based Blocks
Governance	Centralized (Siloed)	Decentralized (Distributed)

4.2 Construction and Serialization of Blockchain-Based Knowledge Graphs

A primary constraint of blockchain technology is its limited capacity for high-volume data storage, which renders the direct uploading of extensive design documentation computationally expensive and inefficient. To circumvent this, we propose a semantic abstraction and serialization framework. By distilling complex design narratives into structured Knowledge Graphs (Figure 7), we capture essential engineering entities and their interdependencies while stripping away linguistic redundancy. These graphs are subsequently serialized into compact JSON-based triples (Entity – Relationship – Attribute), significantly reducing the storage footprint compared to raw text. This "dehydrated" representation allows for the efficient anchoring of design logic onto the blockchain, ensuring data integrity and traceability without compromising system performance. This approach balances the robust security of decentralized ledgers with the practical requirements of large-scale BIM data management.

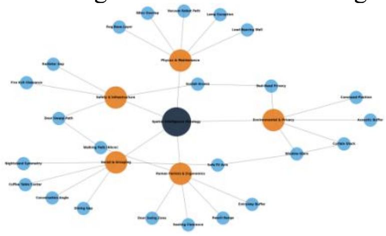

Figure 7. Normalized Knowledge Graph

4.3 Integration of Blockchain-Based Cryptographic Verification in Web-BIM Environment

To circumvent the data redundancy typical of traditional BIM workflows, this study adopts a selective encryption strategy rather than full-scale on-chain storage.he practical implementation within a Web-BIM interface is depicted in Figure 8. As shown in the component property panel, the fields "Knowledge Graph Hash" and "Semantic Ciphertext" confirm that the underlying knowledge graph has been securely processed. Crucially, the geometric data remains decoupled and fully accessible for real-time visualization. This architecture successfully achieves a security-functional decoupling between public geometric representations and private semantic metadata. This ensures that while the model ’ s collaborative utility is preserved, sensitive design intelligence is restricted to authorized stakeholders via blockchain-anchored verification.

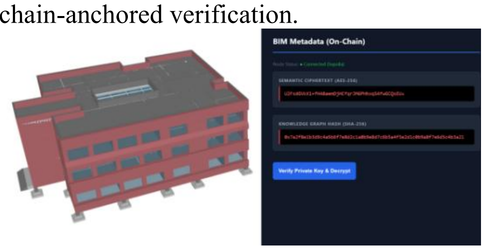

Figure 8. Layered Encryption Display of BIM

5 Experimental Evaluation

This chapter validates the feasibility of the LLM-driven intelligent design framework and the performance of the SE-IFC data structure. The evaluation focuses on three dimensions: layout reliability, computational efficiency, and blockchain-based cryptographic robustness.

The experimental configuration utilized a workstation equipped with an Intel Core i9-13900H CPU and an NVIDIA GeForce RTX 4070 GPU. On the software and model layer, Qwen3.5-4B was employed as the core design engine, while DeepSeek-VL-7B served as the vision-language backbone. The programming environment was developed in Python 3.10, utilizing IfcOpenShell (v0.7.0) for the manipulation of IFC 2×3 standardized files. Blockchain integration and smart contract interactions were implemented using the Web3.py library.

5.1 Reliability Assessment of Intelligent Layout Generation

The intelligent design paradigm proposed in this research fully leverages the generative capabilities of Large Language Models (LLMs), enabling the automated transformation from conceptual descriptions to structured spatial layouts through natural language interaction. However, existing studies predominantly employ traditional Natural Language Processing (NLP) metrics—such as ROUGE-1, ROUGE-2, and ROUGE-L to evaluate model performance. These metrics essentially measure n-gram overlap within text sequences, reflecting the surface-level similarity between generated and reference texts rather than the functional rationality or spatial quality of the final design solutions.

This study shifts the evaluation paradigm from "model performance" to a utility-oriented "design outcome assessment," establishing a multi-variate framework that prioritizes spatial physical performance over linguistic fluency. The proposed framework employs three key metrics to quantify the rationality of LLM-generated layouts: Space Utilization Rate, the Coefficient of Variation in Furniture Spacing, and the Minimum Corridor Width. Specifically, the Space Utilization Rate (SUR) measures the ratio of the total furniture area to the floor area, characterizing the "physical saturation" of the space and reflecting the layout's ability to maximize available area while preventing over-congestion. The calculation is defined in Equation (1):

$$R = \frac{\sum_{i=1}^{n} A_i}{L * W} \tag{1}$$

Where **R** represents the Space Utilization Rate , **A** denotes the total area occupied by furniture, and **L** and **W** represent the width and height of the room, respectively.

The Coefficient of Variation in Furniture Spacing (CV) quantifies the structural order and distribution regularity of the layout by calculating the Euclidean distances between the centroids of all furniture pairs. A lower CV indicates higher spatial uniformity, whereas higher values suggest potential clustering or irregular spacing. The calculation is defined in Equation (2):

$$CV = \frac{\sigma_{dist}}{\mu_{dist}} \tag{2}$$

In this， **CV** denotes the Coefficient of Variation of the layout, μ epresents the mean value of the distances between furniture units, and σ signifies the standard deviation.

The Minimum Corridor Width metric simulates the physical clearance between furniture-to-furniture edges and furniture-to-wall boundaries. To ensure the reliability of the spatial analysis, a rationality filter ranging from 0.3m to 3.0m was implemented. This metric primarily evaluates whether the generated layout preserves sufficient circulation space for human movement and accessibility. The calculation process is defined as follows Equation (3):

$$W_{\min} = \min\{\mathrm{gap(i, j)} \mid \delta < \mathrm{gap} < \mathrm{threshold}\} \tag{3}$$

Admittedly, indoor layout design is a relatively open-ended task with high degrees of freedom; therefore, quantitative metrics alone cannot fully capture the nuances of design quality. To address this, this study randomly sampled 100 representative expert designs from the 3D-FRONT dataset to establish a reference benchmark for reasonable spatial distribution. The LLM was then prompted to generate 10 independent layout iterations. If the metrics of the LLM-generated designs fall within the statistical range of the expert samples, the generative results can be considered to possess a high degree of reliability. The statistical distributions of the three key dimensions are illustrated in Figure 9:

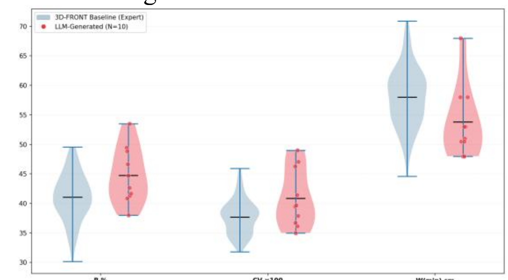

Figure 9. Comparative Distribution of Interior Layout Metrics

Statistical results (Figure 9) indicate that LLM-generated layouts exhibit a high degree of macro-level statistical alignment with expert designs from the 3D-FRONT dataset. Regarding local performance, LLMs enhanced with Retrieval-Augmented Generation (RAG) knowledge bases demonstrate a proactive tendency to increase functional density (e.g., via additional furniture units) to precisely map the multi-scenario requirements defined in user dialogues.

Notably, it was observed that the Minimum Corridor

Width for both expert samples and generated solutions remains within a relatively compact range. This phenomenon is attributed to the inherent spatial constraints of the East Asian residential footprints prevalent in the source dataset. In summary, the current generative model demonstrates remarkable reliability in both semantic synthesis and spatial organization, effectively reaching the statistical thresholds of professional architectural design.

5.2 Storage Overhead Analysis of SE-IFC

To evaluate the SE-IFC framework, we conducted stress tests by scaling metadata by 100x using IfcOpenShell. Storage analysis shows that while a baseline IFC is 3,307 KB, the JSON-serialized semantic layer adds only 79 KB. Due to IFC's internal attribute compression, the integrated package totals 3,349 KB—significantly less than the sum of separate components—confirming minimal storage overhead.

Full-lifecycle loading tests on an i9-13900H workstation (Figure 10) reveal that computational cost is dominated by geometric triangulation (84.3%). The proposed 'Semantic Stream' accounts for only 2.4% of total latency. These results demonstrate that the dual-layer semantic integration achieves seamless model binding with negligible impact on real-time system responsiveness.

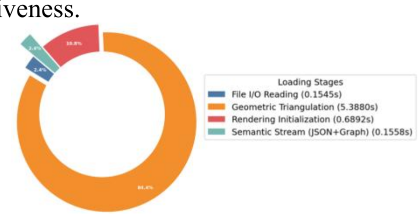

Figure 10. Computational Latency Distribution of the BIM Model Loading Pipeline.

5.3 Evaluation and Performance Analysis of BIM Data Anchoring

In this study, a private Ethereum testnet was established using Ganache, with smart contracts deployed via Remix IDE to simulate a real-world BIM data anchoring environment. The experiment involved batch-encapsulating encrypted JSON data packets containing between 10 and 1,000 RDF triples. We recorded the end-to-end latency, encompassing the entire process of "encryption – signing – consensus-based anchoring – retrieval feedback." As illustrated in Figure 11, the total processing time for up to 1,000 triples remained consistently between 0.03s and 0.06s. These results demonstrate exceptional real-time responsiveness and linear scalability, ensuring that the proposed architecture does not impede high-frequency interactions within BIM models.

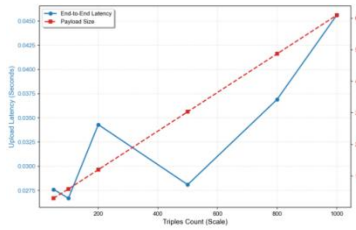

Figure 11. Performance Evaluation of BIM Semantic Data Anchoring

Experimental data further reveals that in a stress-test scenario involving 1,000 BIM semantic triples, the resource consumption for a single anchoring transaction is 1,023,456 Gas. While storage costs on the Ethereum mainnet can be substantial, the smart contracts in this research were authored in Solidity, providing inherent cross-chain interoperability and protocol consistency. This allows the system to dynamically bind to various underlying settlement tokens or blockchain environments (e.g., EVM-compatible Layer 2 solutions or sidechains) based on project budgets and security requirements. In these alternative EVM-compatible environments, the Gas unit price is typically 1% or less than that of the Ethereum mainnet. Consequently, the operational cost for the same scale (1.02M Gas) of BIM data anchoring can be significantly reduced to between 0.07 and 0.28 USD. Given the scale of large-scale construction projects requiring tens of thousands of attribute updates, this cost magnitude offers high economic viability and sustainability.

6 Conclusions and Discussion

In this paper, we propose an IFC semantic enhancement and encryption method driven by large-model generative design. Through a systematic analysis of the semantic features of large-model generative design, we identify key semantic types, structured requirements, and visualization integration elements. The IFC data schema is then extended in a targeted manner, integrating knowledge graph mechanisms to increase semantic coverage while maintaining compatibility with BIM software. Additionally, we design an encryption verification process using smart contracts and encryption algorithms to ensure the security of IFC design data during transmission.

The innovation of this study lies in integrating AI technology with the traditional BIM storage architecture, effectively addressing the limitations of traditional IFC in handling complex design semantics. This approach offers a new perspective for the intelligent transformation of architectural design.

Regarding the inherent limitations of Large Language Models (LLMs) in executing complex architectural design tasks, both academia and industry have bifurcated into two primary evolutionary trajectories: the "Harness-oriented" approach and the "Model-oriented" approach. The former advocates for the construction of multi-level, progressive skill sets and knowledge base systems to constrain model outputs through external logic. Conversely, the latter focuses on enhancing the domain-specific reasoning capabilities of the models themselves via domain pre-training and fine-tuning.

This study posits that, compared to the standardized environments of code generation, the challenges of "regulatory abstraction" and "data sparsity" within the architectural design domain are significantly more profound. As noted by industry leaders such as Anthropic (Claude), the acquisition and structural complexity of high-quality architectural drawing data far exceed those of general-purpose code datasets. Consequently, developing a robust "External Architectural Framework"—rather than relying solely on increasing model scale—is of paramount importance for enhancing the practical utility of LLMs in the AEC (Architecture, Engineering, and Construction) sector.

The research focus of this study consistently aligns with the "Harness-oriented" (Architectural Augmentation) pathway, dedicated to constructing a comprehensive automated upgrade system. The specific strategies are as follows:

Multi-stage Task Decomposition: By constructing hierarchical systems and serialized command streams, this approach effectively mitigates "attention dispersion" and "logical drift" caused by excessive one-time context injection. This ensures the stability of the generative process across complex design sequences.

Multi-Agent Cooperation Architecture: The framework introduces functionally diverse Agents for parallel processing and cross-verification, establishing a robust error-correction mechanism.

Acknowledgments

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