A structured Prompt Engineering Framework for Modular Construction Design Using Generative AI

Zaid Alwashah[1], Bo Xiao[2], Hexu Liu[1], Xiaoyun Shao[1], and Xiaoman Wang[3]

[1]Department of Civil and Construction Engineering, Western Michigan University, Michigan, USA
[2]Department of Civil, Environmental, and Geospatial Engineering, Michigan Technological University, Michigan, USA
[3]Department of Educational Leadership, Research and Technology, Western Michigan University, Michigan, USA

zaid.alwashah@wmich.edu, boxiao@mtu.edu, hexu.liu@wmich.edu, xiaoyun.shao@wmich.edu, xiaoman.wang@wmich.edu

Abstract –
The modular construction industry requires early and tightly coupled reasoning across spatial layout, structural systems, module interfaces, and building services under fabrication, transportation, and assembly constraints. With recent advances in generative artificial intelligence (AI) and the emergence of large language models (LLMs), there is growing interest in leveraging these technologies to support design reasoning through natural language interaction. However, existing studies lack domain-specific methodologies that systematically translate modular design reasoning into effective prompts for generative AI systems. This study addresses this gap by introducing a reasoning-oriented taxonomy of modular construction design tasks and a structured prompt engineering framework tailored to modular design contexts. The proposed framework formalizes prompt construction through standardized blocks and demonstrates its application using representative prompts grounded in a modular residential case study. The proposed framework provides a methodological foundation for reasoning-aware human–AI interaction in early-stage modular construction design.

Keywords –
Modular Construction; Prompt Engineering; Large Language Models; Design Reasoning; BIM

1 Introduction

Modular construction has gained increasing attention as an alternative to conventional on-site construction due to its potential to improve productivity, quality control, and construction safety by shifting substantial portions of the building process from site environments to controlled factory settings [1], [2]. Prior research consistently indicates that off-site and modular construction can reduce schedule uncertainty, enhance manufacturing precision, and mitigate safety risks associated with labor-intensive site activities, particularly in residential and mid-rise building projects [3], [4]. Despite these advantages, modular construction introduces a distinct set of design and coordination challenges that differ fundamentally from traditional cast-in-situ construction. Modular projects require early and tightly coupled reasoning across spatial layout, structural systems, module interfaces, and building services to ensure manufacturability, transportability, and on-site assembly feasibility [1], [5]. Errors or inconsistencies introduced during the early design stages are difficult and costly to correct once production has commenced, highlighting the importance of structured, front-loaded design decision-making [6]. Building Information Modeling (BIM) has been widely adopted to support modular and off-site construction by enabling the integrated representation of geometry, components, and construction information across disciplines [2], [7]. However, prior BIM-based approaches largely rely on manual modelling, rule-based automation, or discipline-specific scripts, which remain time-consuming and require significant expert input [8], [9], [10]. As a result, BIM tools alone provide limited support for the reasoning-intensive nature of early modular design, where designers must iteratively explore layout configurations, assess structural logic, and anticipate inter-module and service coordination constraints.

Recent advances in generative artificial intelligence (AI), particularly large language models (LLMs), have demonstrated strong capabilities in interpreting natural language instructions, supporting design reasoning, and generating structured responses across complex problem domains [11], [12]. In parallel domains, LLM performance has been shown to depend strongly on prompt formulation, with structured prompt engineering strategies significantly improving reasoning quality, consistency, and controllability [13], [14].

Within the construction and BIM context, emerging studies have begun exploring the use of LLMs for tasks such as automated compliance checking, design interpretation, and limited forms of reasoning support [11], [15]. However, current LLM research in the AEC and BIM space is still reported largely as isolated, task-level prototypes, such as BIM information search assistants, schedule or sequence generation, and chatbot-style query systems, rather than as reusable prompting methodologies that generalize across design reasoning tasks [16]. Moreover, recent AEC reviews explicitly note that outcomes are highly prompt-dependent, yet the prompt practices documented across studies vary widely (e.g., template-based, few-shot, role-based, chain-of-thought, iterative prompting), indicating limited consolidation into a consistent and transferable prompting approach for design reasoning [16], [17], [18], [19]. As a result, there is limited guidance on how to systematically translate reasoning-intensive modular design problems, such as the coupling of layout, structure, interfaces, and MEP systems under fabrication and transport constraints, into robust prompt structures that can be reused across modular design stages.

To address this gap, this study proposes a structured prompt engineering approach tailored to modular construction design. The research contributes (1) a task taxonomy that categorizes modular design activities based on their dominant reasoning requirements, (2) a structured prompt engineering framework that formalizes how modular design tasks can be expressed as prompts, and (3) representative prompt examples grounded in a realistic modular residential design scenario. Rather than evaluating model performance, the focus of this work is on clarifying the relationship between modular design reasoning and prompt structure, thereby providing a foundational framework for future generative AI applications in modular construction design.

2 Literature Review

Prior research on modular and off-site construction has primarily emphasized process optimization, production efficiency, and lifecycle performance. Reviews of prefabricated and modular construction management consistently highlight that modular projects require earlier design finalization and stronger cross-disciplinary coordination than conventional construction, due to the interdependence between manufacturing, transportation, and on-site assembly decisions [3], [4]. These studies emphasize that design decisions related to layout, structural systems, and service integration must be resolved up front to avoid costly rework once factory production begins, underscoring the reasoning-intensive nature of early modular design stages. Moreover, BIM has been widely adopted for providing integrated digital representations of building geometry, components, and construction information. Prior studies demonstrate that BIM facilitates coordination across design and construction disciplines in modular and off-site projects, enabling improved visualization, clash detection, and constructability analysis [2], [20]. Recent advancements in AI within construction engineering have introduced data-driven and learning-based approaches for design support, optimization, and automation. These applications commonly employ knowledge-based and machine-learning techniques for planning, monitoring, and decision support. These approaches often rely on predefined rules or structured project data (e.g., BIM/event logs), and several methods still face constraints such as limited adaptability and knowledge acquisition bottlenecks [21], [22]. These limitations are particularly pronounced in conceptual design contexts, where problem definitions are incomplete and reasoning requirements evolve dynamically.

More recently, generative AI and LLMs have demonstrated strong capabilities in interpreting natural language, generating structured outputs, and supporting reasoning-oriented tasks across engineering domains. Studies in engineering design report that LLMs can assist with concept generation, explanation, and design reasoning, particularly when problems are expressed in well-structured textual forms [23]. Within the construction and BIM domain, early investigations have applied LLMs to automated compliance checking and information retrieval tasks, showing that natural language interfaces can improve accessibility to BIM data and rule interpretation [15], [24]. However, these applications primarily focus on downstream validation or query tasks rather than upstream design reasoning.

Parallel research in prompt engineering has shown that LLM performance is highly sensitive to how tasks are framed. Studies indicate that structured prompt formulations, including explicit context definition, constraint specification, and reasoning objectives, significantly improve model reliability, interpretability, and reasoning depth [14], [25]. Design tasks differ from conventional NLP benchmarks in that they require spatial reasoning, constraint satisfaction, and multi-objective trade-off exploration. However, prompt engineering research remains largely domain-agnostic, offering limited guidance on how domain-specific reasoning tasks, such as those in modular construction design, should be translated into effective prompts. This limitation is critical for modular construction design, where early-stage decisions must simultaneously satisfy manufacturability, transportation, and assembly constraints. Within modular construction research, computational design studies increasingly recognize the need for integrated reasoning across layout, structure, and services.

Taken together, the literature reveals a clear gap at the intersection of modular construction design, BIM-based workflows, and generative AI. While BIM provides an integrated data environment and LLMs offer powerful natural language reasoning capabilities, there is limited research on how modular design tasks can be systematically translated into structured, reasoning-oriented prompts that align with both domain constraints and principles of prompt engineering. This gap motivates the development of a domain-specific prompt engineering framework that explicitly connects modular design task characteristics with structured prompt formulations, enabling more effective use of generative AI during early modular design stages.

3 Research Methodology

This study adopts a design-oriented methodological approach to develop a structured prompt engineering framework grounded in modular construction design reasoning. The methodology systematically organizes modular design tasks and links design reasoning requirements to prompt formulation for generative AI systems. Figure 1 presents an overview of the research methodology.

The methodology consists of four sequential steps. First, modular design reasoning was analyzed using insights from modular and off-site construction literature and the representative case, identifying key design reasoning characteristics that distinguish modular construction from conventional building design, particularly in early design stages. These reasoning characteristics highlight the need for early coordination across spatial layout, structural systems, module interfaces, and building services under fabrication and transportation constraints. Second, building on the reasoning characteristics identified in Step 1 and the analysis of a representative modular residential scenario, modular construction design activities were decomposed and organized into a reasoning-oriented task taxonomy. For example, in the representative modular residential scenario (Section 6), the need to maintain vertical alignment of wet areas across stacked units, such as bathrooms and kitchens, was identified in Step 1 as a key reasoning constraint and formalized in Step 2 under layout and MEP coordination tasks. The taxonomy emphasizes core reasoning dimensions, such as spatial layout logic, structural continuity, module connection consistency, and building service coordination, rather than software tools or implementation-specific modelling techniques.

Third, the task taxonomy developed in Step 2 was used as a conceptual bridge to structure prompt formulation, drawing on established prompt engineering concepts such as context specification, explicit task definition, constraint articulation, and expected output structuring. This step resulted in a structured prompt engineering framework linking modular design task characteristics with prompt components and reasoning objectives. Finally, a representative modular residential case study was used to illustrate the application of the proposed taxonomy and structured prompt engineering framework. This step demonstrates how modular design tasks are translated into reasoning-oriented prompts, clarifying the coherence and applicability of the proposed approach, as detailed in Sections 4–6 corresponding to the task taxonomy, structured prompt framework, and case study components of the methodology (Figure 1).

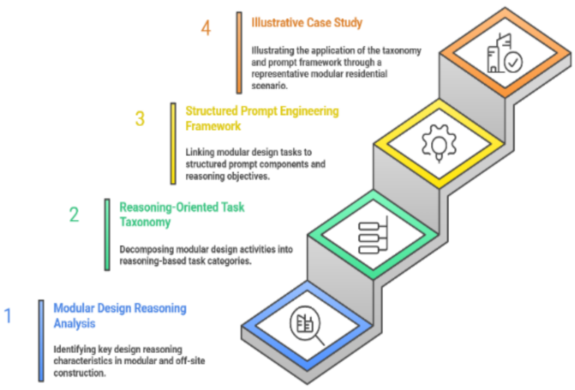

Figure 1. Research workflow for developing the prompt engineering framework.

4 Modular Construction Design Task Taxonomy

Modular construction design consists of a set of interconnected tasks that differ significantly from traditional on-site building design. This distinction stems from the production-oriented nature of modular construction, which requires off-site fabrication, transportation, and on-site assembly. Consequently, coordinated reasoning is needed for spatial layout, structural systems, inter-module connections, and building services, including zoning rooms within transport-constrained module envelopes, maintaining load-path continuity across stacked modules, aligning module interfaces for vertical stacking, and preserving vertical continuity of building services. As a result, design effort is shifted toward early-stage reasoning and decision-making rather than downstream detailing. Given this level of interdependence, the effective use of generative AI in modular construction relies on understanding the types of design tasks and associated reasoning processes needed. In response to this need, this study presents a taxonomy of modular construction design tasks that organize these activities based on their primary reasoning requirements. The taxonomy is derived from a realistic modular residential design using a design decomposition approach, in which design decisions, constraints, and coordination requirements were identified and iteratively grouped according to their dominant reasoning characteristics. Task categorization was guided by the primary reasoning required to resolve each requirement, including spatial layout, structural continuity, module interface coordination, and building service integration. This approach ensures conceptual consistency across task categories and supports direct mapping between design reasoning and prompt formulation. To emphasize reasoning over implementation details, the taxonomy organizes modular design into reasoning-driven categories rather than software-specific modelling processes. Accordingly, Figure 2 presents the proposed modular construction design task taxonomy, derived through design decomposition of the case scenario, illustrating how design decisions, constraints, and coordination requirements are grouped based on their dominant reasoning characteristics and serving as the foundation for the prompt engineering framework introduced in the following section.

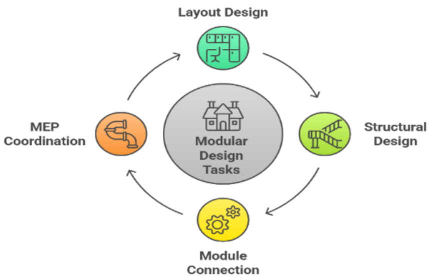

Figure 2. Reasoning-oriented task taxonomy derived from modular design decomposition.

Layout design tasks address spatial zoning, circulation organization, room adjacency logic, and compliance with transport envelopes and minimum dimensional requirements. In contrast, structural design tasks focus on framing logic, load-path continuity, and structural consistency across stacked modules, particularly under conditions of transport, lifting, and in-service use (e.g., maintaining vertical load transfer across module boundaries). Building upon these considerations, module connection tasks involve reasoning about vertical stacking alignment, horizontal joining strategies, continuity of load transfer surfaces, and fire or acoustic separation across module interfaces (e.g., alignment tolerances at vertical module interfaces). In parallel, MEP coordination tasks address service zoning, plumbing stack alignment, clash awareness, and continuity of building services across modules (e.g., preserving vertical service continuity across stacked units).

5 Structured Prompt Engineering Framework

Modular construction tasks differ in scope and complexity; therefore, their effective use of generative AI systems relies on how these tasks are converted into prompts. Unstructured prompts often lead to unclear or incomplete reasoning, particularly under modular fabrication and transportation constraints. To tackle this issue, this study proposes a structured prompt engineering framework specifically for modular construction design tasks. Figure 3 illustrates the proposed framework, showing how modular design tasks are translated into structured prompts through standardized prompt blocks and instantiated as different prompt types depending on the intended reasoning objective. The framework standardizes how prompts are created by breaking each prompt into a set of functional blocks that guide AI reasoning and minimize ambiguity. It is intentionally not tied to any specific tool and aims to support design reasoning across various generative AI systems, including general-purpose LLMs and BIM-integrated design assistants.

Each prompt is composed of five core elements. A Context Block defines the modular design scenario, including building type, modular system characteristics, and high-level constraints. A Task Definition Block explicitly states the intended action, such as generating, analyzing, checking, or revising a design aspect. A Constraints Block specifies relevant dimensional, structural, code-related, or modular limitations that must be respected. An Expected Output Block defines the desired response format, such as structured text, stepwise reasoning, or descriptive lists. Finally, a Validation and Guardrails Block requests explicit checks for known failure points or critical conditions, discouraging unsupported assumptions or hallucinated design elements. The five core blocks serve as a reference structure rather than a rigid template, allowing prompt configurations to be adapted, simplified, or extended in accordance with task complexity and specific reasoning requirements.

Using this structure, modular design tasks can be systematically linked to different prompt types, such as directive prompts for generation, analytical prompts for explanation, diagnostic prompts for checking consistency, and corrective prompts for refinement. Each prompt type emphasizes a different reasoning objective while retaining the same underlying block structure.

Reusable prompt templates are created by filling in the structured blocks with task-specific information and constraints, allowing for consistent prompt development across various modular design scenarios and supporting iterative prompt reuse as design objectives evolve.

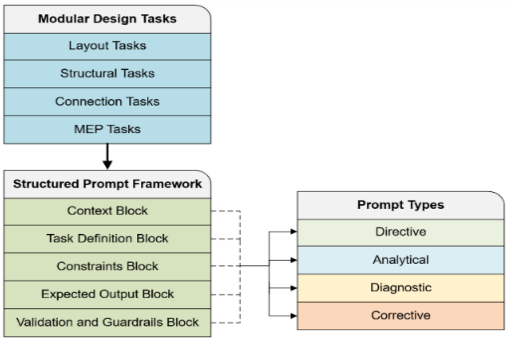

Figure 3. Structured prompt engineering framework for modular construction design tasks

6 Modular Case Study and Prompt Instantiation

This section presents a representative modular residential case study that demonstrates how the proposed task taxonomy and prompt engineering framework can be applied in practice. The purpose of the case study is not to validate the performance of automated modelling or generate construction-ready outputs, but rather to provide a realistic design context for prompt formulation and reasoning-based interaction with generative AI systems.

6.1 Scenario Definition

The demonstration scenario is based on a low-rise residential building composed of vertically stacked modular units, representative of common volumetric modular construction practices. The building configuration consists of two primary above-grade levels organized around a central circulation core, with repeated and aligned spatial layouts across floors. A sectional axonometric view of the case study is shown in Figure 4, illustrating the stacked modular arrangement, floor separation, and overall spatial organization. The internal program reflects a typical residential layout, including living, dining, and kitchen spaces on the lower level, and bedroom and bathroom spaces on the upper level. Wet areas and service zones are vertically aligned, reflecting common modular strategies that support service continuity and inter-module coordination. The scenario is constrained by module dimensions and the need for vertical alignment of structural and service elements across stacked units. Structural and MEP systems are represented at a conceptual level to highlight coordination logic, interface relationships, and service alignment, without implying finalized engineering specifications.

Figure 4. Modular residential case illustrating design stages aligned with task categories and prompt types

6.2 Example Prompts Based on Modular Design Tasks

Using the modular residential scenario illustrated in Figure 4, a set of representative prompts was created to demonstrate how the modular design task taxonomy (Section 4) can be operationalized using the structured prompt engineering framework introduced in Section 5. The examples presented in this section are designed to show how different modular design tasks can be translated into clear, reasoning-oriented prompts suitable for generative AI systems.

Although the representative prompts are expressed at an abstract level, they are implicitly grounded in the modular residential scenario described in Section 5.1, including vertically stacked units, aligned wet areas, centralized circulation, and transport-constrained module dimensions. These scenario characteristics inform the intent and constraints of each prompt without requiring explicit numerical parameterization.

Each example prompt follows a consistent structure, including a clearly defined context, an explicit task specification, relevant modular constraints, and an articulated expected output and validation intent. This structure enables a direct mapping between the modular design task categories (layout, structural, module connection, and MEP coordination) and the corresponding prompt types (directive, analytical, diagnostic, and corrective) defined in the proposed framework. In this mapping, the task category specifies the design aspect under consideration (e.g., layout or structure), the prompt type defines the intended reasoning action (e.g., generation or diagnosis), and the structured prompt blocks provide the mechanism for expressing this intent in a consistent and explicit form.

Table 1 summarizes the representative prompts used in this study, illustrating how each modular design task category is paired with an appropriate prompt type and expressed as a concise, reasoning-oriented instruction. The examples in Table 1 demonstrate how abstract modular design tasks can be systematically translated into clear and reusable prompts suitable for generative AI systems, while maintaining alignment with the reasoning-driven taxonomy presented earlier.

Table 1. Representative prompts mapped to modular design task categories and prompt types (presented as concise, illustrative instructions)

Task Category	Prompt Type	Representative Prompt
Layout	Directive	Generate a spatial layout for a transport-constrained modular unit that minimizes corridor length while preserving privacy and maintaining vertical alignment of wet areas and service zones.
Structural	Analytical	Explain how load-path continuity can be maintained across vertically stacked modular units, including across module interfaces.
Connection	Diagnostic	Identify potential alignment issues at vertical module interfaces in a stacked modular configuration.
MEP	Diagnostic	Check whether the layout supports vertical continuity of plumbing and mechanical services across modules.

To further illustrate the added value of the proposed task taxonomy and structured prompt engineering framework, the following expanded example demonstrates how a modular design task can be systematically translated into an explicit, reusable prompt structure, rather than relying on ad hoc or user-specific prompt formulations, using a directive layout design task based on the modular residential scenario in Figure 4. For clarity, the representative prompts in Table 1 are intentionally expressed in concise form, whereas the expanded example below demonstrates how a single prompt can be fully instantiated using the same block structure defined in Section 4, without loss of generality across other prompt types.

Context Block: Consider a low-rise residential building composed of vertically stacked modular units with aligned floor layouts, centralized circulation, and vertically continuous wet areas, representative of the modular configuration shown in Figure 3.

Task Definition Block: Generate a conceptual spatial layout for a single modular unit that supports the overall building configuration and preserves the stated stacking and service-alignment logic across levels.

Constraints Block: The layout must respect transport-constrained module dimensions, preserve privacy between primary living and sleeping spaces, and maintain vertical alignment of wet areas and service zones across stacked units.

Expected Output Block: Provide a stepwise explanation of the proposed layout strategy, describing room zoning, circulation organization, and service alignment logic.

Validation and Guardrails Block: Verify that the proposed layout maintains vertical service continuity of wet areas and service zones, avoids introducing structural claims not supported by the stated scenario, and does not introduce spaces that violate modular transport or stacking constraints.

6.3 Implications of Structured Prompting for Modular Design Tasks

The examples presented in Section 6.2, grounded in the modular residential scenario illustrated in Figure 4 and summarized in Table 1, demonstrate how modular design tasks can be systematically translated into structured prompts, providing a common and repeatable way to express design reasoning that does not depend solely on individual user experience or personal prompt-writing skills by decomposing each task into explicit context, task intent, constraints, expected outputs, and validation objectives, the proposed framework transforms implicit design reasoning into more transparent, communicable, and reusable representation for interaction with generative AI systems.

From a modular design perspective, this structured prompting approach supports clearer separation between different types of design reasoning. Layout tasks emphasize spatial organization and adjacency logic, structural tasks focus on continuity and alignment across stacked modules, connection tasks highlight interface consistency, and MEP coordination tasks address service zoning and vertical continuity. The framework offers a consistent vocabulary and structure for expressing modular design intent, rather than relying on ad hoc or experience-driven prompt formulations.

More broadly, the framework contributes a task-driven method for prompt formulation in modular construction design. Rather than treating prompts as isolated or tool-specific inputs, the proposed approach frames them as reusable design artifacts that encode domain knowledge and reasoning expectations. This supports knowledge transfer across designers, projects, and design stages, and offers a conceptual foundation for future integration with BIM-based workflows, design assistants, and decision-support tools, without requiring immediate automation or performance benchmarking. In a BIM-integrated context, the proposed framework can act as an intermediate reasoning layer between structured BIM data and generative AI systems. Inputs may be extracted from model properties, schedules, or IFC-based representations (e.g., space lists, module grids, dimensional envelopes, and coordination zones) and translated into prompt context and constraints. The resulting outputs represent structured reasoning responses, such as layout recommendations or coordination checks, which can be mapped back to BIM actions including model revision, alignment validation, and issue identification.

7 Conclusion

This study addressed a critical gap at the intersection of modular construction design, BIM-based workflows, and generative AI by proposing a domain-specific prompt engineering framework grounded in modular design reasoning. Modular construction demands early and integrated decision-making across layout, structure, module connections, and building services, yet existing AI and BIM-based approaches provide limited guidance on how such reasoning-intensive tasks should be translated into effective prompts for generative AI systems.

To respond to this challenge, the study first developed a reasoning-oriented taxonomy of modular construction design tasks, derived from a production-oriented residential modular scenario. By organizing modular design activities according to their primary reasoning requirements rather than implementation tools or modelling techniques, the taxonomy establishes a conceptual bridge between modular design logic and prompt formulation. Building on this foundation, a structured prompt engineering framework was introduced, defining a consistent set of prompt blocks and linking modular design tasks to distinct prompt types aligned with different reasoning objectives.

The Framework was illustrated through a representative modular residential case study and a set of example prompts, including a fully instantiated prompt demonstrating how contextual information, constraints, and validation objectives can be explicitly encoded. These examples illustrate how structured prompting can represent modular design reasoning as clear, reusable instructions suitable for interaction with generative AI systems, without requiring construction-ready outputs or performance benchmarking. The primary contribution of this work lies in its methodological framing rather than technical evaluation. By explicitly connecting modular design reasoning with structured prompt engineering principles, the proposed approach supports more transparent and controllable human–AI collaboration during early-stage modular design. Future research may extend this framework by applying it to additional building typologies, integrating it with BIM-based design assistants, or empirically evaluating its impact on design quality, efficiency, and user trust in generative AI–supported modular construction workflows. While the proposed framework provides a structured approach to prompt formulation, its impact on reasoning quality and performance has not been quantitatively evaluated in this study and remains an important direction for future research.

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