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Research Article

Keywords: Generative AI, Multi-Agent Systems, Autonomous Building Design, Structural Planning, Building Layout Optimization, Artificial Intelligence, Civil Engineering

Posted Date: October 13th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11321926/v1>

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Additional Declarations: The authors declare no competing interests.

Smart Autonomous Building Design and Physical-Informed Structural Planning using Generative Multi-Agent Systems

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1 Abstract

The rapid growth of urbanization has increased the need for intelligent, efficient, and sustainable building design and planning solutions. Traditional building design processes often require significant time, manual effort, and coordination among architects, structural engineers, planners, and other experts. This project, “Smart Autonomous Building Design and Planning Using Generative Multi-Agent Systems,” proposes an intelligent framework that automates and improves the building design and planning process using Artificial Intelligence (AI) and collaborative multi-agent systems.

The proposed system collects input data such as plot dimensions, site information, user requirements, number of rooms, building constraints, environmental conditions, and budget preferences. Multiple specialized AI agents, including a Planning Agent, Architectural Design Agent, Structural Analysis Agent, Sustainability Agent, and Cost Estimation Agent, collaborate to generate and evaluate possible building designs. A Generative AI-based design engine produces optimized floor plans and building layouts based on the collected requirements.

The generated designs are evaluated using important parameters such as space utilization, structural feasibility, cost efficiency, energy efficiency, sustainability, and compliance with user-defined constraints. If a generated design does not satisfy the required conditions, the system performs an iterative optimization process to modify the design parameters and generate improved alternatives. The final optimized design can be presented through floor plans and digital visualization.

The proposed system aims to reduce manual design effort, improve coordination between different design tasks, and support faster and more intelligent decision-making. By integrating Generative AI with multi-agent collaboration, this project provides a scalable and intelligent approach toward autonomous, efficient, and sustainable building design and planning.

2 Introduction:

The construction and building design industry is undergoing significant transformation due to the increasing demand for intelligent, efficient, and sustainable infrastructure. Building design and planning traditionally involve multiple stages, including requirement analysis, site planning, architectural design, structural analysis, cost estimation, and environmental assessment. These processes often require collaboration among different professionals and can be time-consuming and complex.

Artificial Intelligence (AI) has the potential to improve this process by automating repetitive tasks and supporting intelligent decision-making. In particular, Generative AI can automatically generate multiple design alternatives based on predefined requirements and constraints. However, building design involves several interconnected domains, making it difficult for a single system to handle all aspects effectively.

The proposed project, “Smart Autonomous Building Design and Planning Using Generative Multi-Agent Systems,” introduces a collaborative AI-based framework in which multiple specialized agents work together to perform different building design tasks. The system includes agents responsible for planning, architectural design, structural evaluation, sustainability analysis, cost estimation, and coordination.

The proposed system takes various input parameters, such as plot dimensions, site information, number of floors, room requirements, user preferences, budget constraints, environmental

conditions, and building regulations. Based on these inputs, the Generative Multi-Agent System generates possible building layouts and evaluates them according to different performance criteria.

3 Literature Review:

Sr. No.	Authors & Year	Primary Focus & Methodology	Relevance to Problem Statement	Key Takeaways for Proposed Framework
1	Li et al. (2024)	Automated architectural space-layout planning using a physics-inspired generative design framework and evolutionary optimization.	Addresses the time-consuming nature of manual architectural layout planning and incorporates physical constraints into layout generation.	Supports the proposed Architectural Agent and physics-inspired generative layout optimization.
2	He, Wang & Zhang (2025)	Generative AIBIM, integrating BIM and Generative AI with a two-stage generation framework and physics-based conditional diffusion model.	Addresses automated structural design and integration of physical conditions with Generative AI.	Provides a foundation for combining Generative AI + BIM + Physics-Informed Structural Planning.
3	Jeong et al. (2023)	Physics-Informed Neural Network (PINN) framework for structural topology optimization.	Addresses limitations of purely data-driven AI by incorporating physical knowledge into structural optimization.	Supports the proposed Structural Agent and physics-informed structural validation.
4	Jiang et al. (2025)	Review of Physics-Informed Machine Learning for Building Performance Simulation, focusing on physical consistency, optimization, and building performance.	Highlights limitations of purely data-driven models and the importance of physical knowledge in building AI systems.	Supports physics-informed constraints, sustainability analysis, and performance optimization.
5	Murphy et al. (2026)	Scoping review and categorization of Physics-Informed Machine Learning in Structural Engineering.	Identifies challenges in integrating physical knowledge with machine learning for structural engineering.	Reinforces the need for a unified framework combining AI generation, structural physics, validation, and optimization.
6	Jeong et al. (2023)	Complete PINN-based topology optimization (CPINNT0) using PINNs for structural and sensitivity analysis in 2D and 3D structures.	Reduces dependence on conventional computational structural analysis while maintaining physical consistency.	Supports automated physics-based structural analysis and iterative optimization.
7	Wu et al. (2023)	Surrogate-based Physics-Informed Neural Network for structural optimization, combining neural networks, surrogate analysis, and optimization.	Addresses the computational cost of repeated structural analysis during optimization.	Supports the Structural Agent + Optimization Agent for faster design evaluation and refinement.
8	Singh, Chakraborty & Chowdhury (2024)	Dual Physics-Informed Neural Network for topology optimization of 2D and 3D structural problems.	Combines physics-informed learning with structural optimization to improve physical feasibility.	Supports a physics-informed optimization layer for structural design constraints.
9	He, Wang & Zhang (2023)	Generative AIBIM, combining BIM, Generative AI, and physics-based conditional diffusion for automated structural design.	Addresses the gap between generative design and physically feasible structural design.	Demonstrates the potential of Generative AI + BIM + physical constraints for autonomous building design.
10	Wu et al. (2024)	Physics-informed AI and surrogate modeling approaches for structural design optimization and efficient engineering analysis.	Addresses computational efficiency and the need for physically consistent AI-generated structural solutions.	Supports fast structural evaluation, optimization, and multi-agent design refinement.

Table 1. Summary of Literature Review

4 Methodology

• A. Proposed Methodology and System Architecture

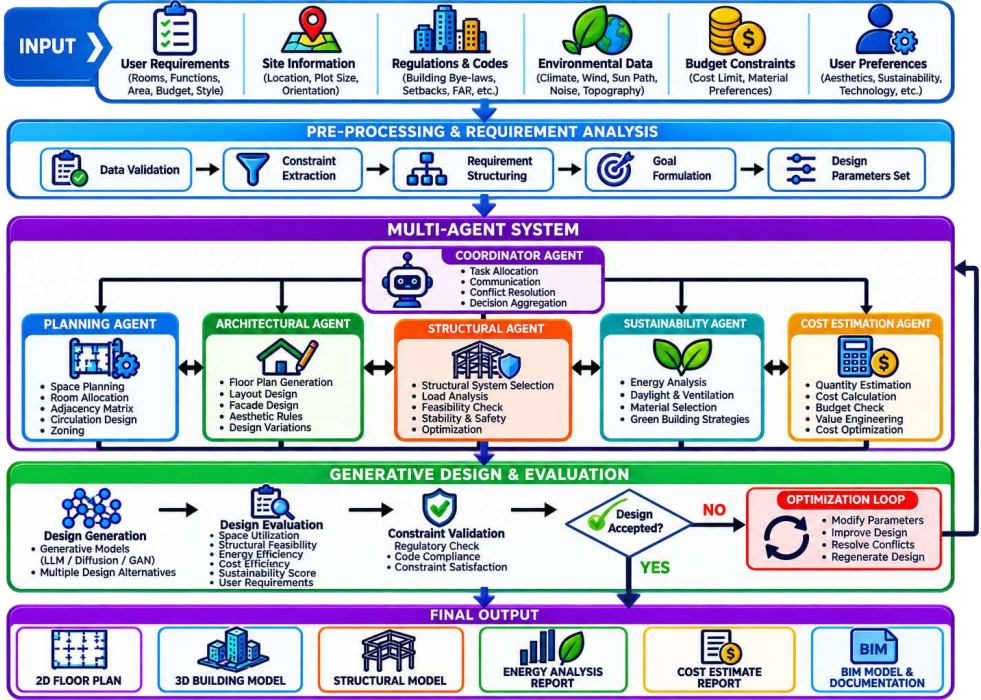


Fig. 1. Proposed Methodology Framework for Autonomous Building Design

The proposed Smart Autonomous Building Design and Planning System Using Generative Multi-Agent Systems follows a structured and collaborative Artificial Intelligence-based architecture. The system integrates requirement analysis, specialized AI agents, generative design, evaluation, optimization, and final building design generation. The overall framework is illustrated in Figure 1.

4.0.1 User Input Module: The User Input Module collects essential building requirements, including plot size, number of floors, room requirements, budget, building type, design constraints, user preferences, and local building regulations. These requirements define the functional and technical specifications of the proposed building.

4.1 Pre-Processing and Requirement Analysis

The collected input data undergoes pre-processing and requirement analysis before being provided to the multi-agent system. The major activities include:

- (1) **Data Validation:** The system verifies the completeness and correctness of the collected information.
- (2) **Constraint Extraction:** Important design constraints are identified from user requirements, site information, and regulatory rules.
- (3) **Requirement Structuring:** The unstructured input requirements are converted into a structured representation that can be processed by AI agents.

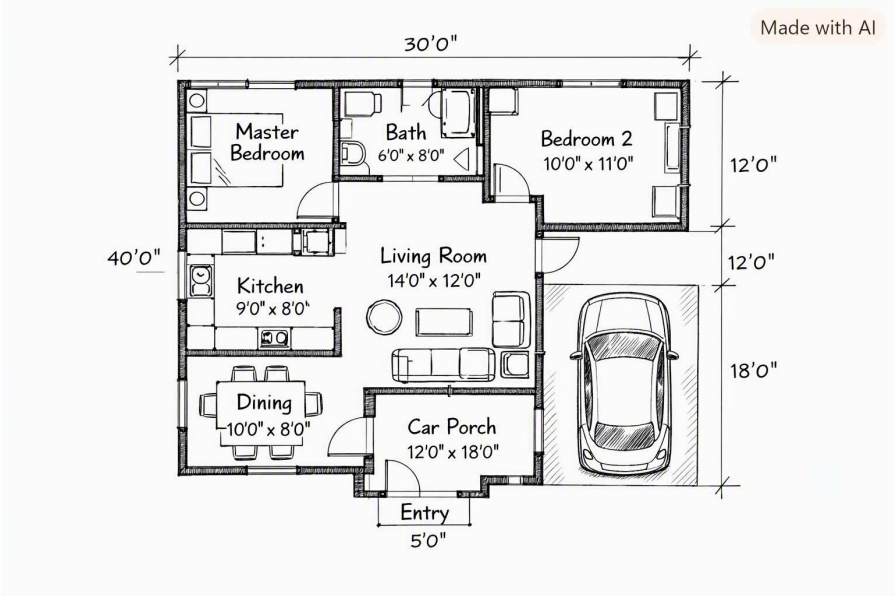


Fig. 2. Representative 2BHK Architectural Floor Plan Layout (30' × 40') showing spatial arrangement and key functional zones.

- (4) **Goal Formulation:** The primary design objectives are identified, such as maximum space utilization, cost efficiency, structural safety, energy efficiency, sustainability, and user satisfaction.
- (5) **Design Parameter Setting:** The system establishes the design parameters required for generating building alternatives.

4.2 Multi-Agent System

The core component of the proposed framework is the Multi-Agent System, where multiple specialized AI agents collaborate to perform different building design tasks.

4.2.1 *Coordinator Agent.* The Coordinator Agent acts as the central control component of the system. Its major responsibilities include task allocation, communication between agents, conflict resolution, and decision aggregation. The Coordinator Agent ensures effective collaboration among all specialized agents.

4.2.2 *Planning Agent.* The Planning Agent is responsible for the initial spatial planning of the building. Its functions include space planning, room allocation, adjacency matrix generation, and circulation design. This agent ensures that the functional requirements of the building are properly organized.

4.2.3 *Architectural Agent.* The Architectural Agent generates the architectural design and layout of the building. Its major tasks include floor plan generation, layout design, facade design, application of aesthetic rules, and generation of multiple design alternatives.

4.2.4 *Structural Agent.* The Structural Agent evaluates the structural feasibility of the generated building design. Its responsibilities include structural system selection, load analysis, feasibility

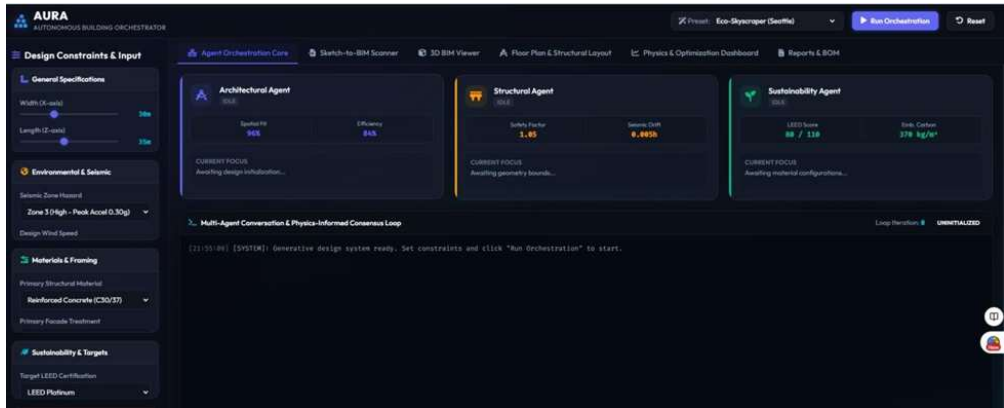


Fig. 3. Autonomous Building Orchestrator Dashboard displaying agent orchestration core (Architectural, Structural, and Sustainability Agents) and design constraint parameters.

checking, and stability and safety assessment. The agent ensures that the generated architectural design satisfies essential structural requirements.

4.2.5 Sustainability Agent. The Sustainability Agent evaluates the environmental performance of the building design. Its functions include energy analysis, daylight analysis, ventilation assessment, material selection, and green building strategy recommendation. This agent helps generate environmentally responsible building designs.

4.2.6 Cost Estimation Agent. The Cost Estimation Agent analyzes the economic feasibility of the generated building design. Its major functions include quantity estimation, construction cost calculation, budget checking, and value engineering. This ensures that the proposed design remains within the specified budget constraints.

4.3 Generative Design Process

After multi-agent analysis, the system performs the generative design process. AI-based generative models are used to create multiple possible building design alternatives. The generated designs consider user requirements, site constraints, architectural requirements, structural feasibility, environmental conditions, and budget limitations. The system generates multiple alternatives instead of relying on a single design solution.

4.4 Design Evaluation

Each generated building design is evaluated using multiple performance parameters. The major evaluation criteria include space utilization, structural feasibility, energy efficiency, cost efficiency, sustainability score, and user requirement satisfaction. The specialized agents provide feedback regarding the performance of each design alternative.

4.5 Constraint Validation

The generated designs are validated against predefined requirements and constraints. The validation process checks regulatory compliance, building code compliance, structural constraints, budget limitations, and user-defined requirements. This stage ensures that the generated design is practically feasible.

4.6 Design Acceptance and Optimization Loop

After evaluation, the system determines whether the generated design satisfies the required conditions.

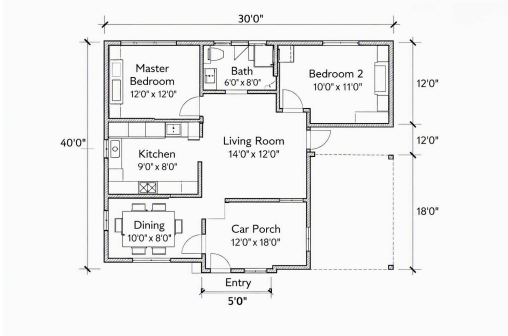
- **If the design is accepted:** The system proceeds toward the generation of the final building design.
- **If the design is not accepted:** The system enters an Optimization Loop.

The optimization process modifies design parameters, improves the building design, resolves conflicts between requirements, and regenerates design alternatives. This iterative process continues until an optimized and acceptable design is obtained.

4.7 Final Output Generation

After successful evaluation and optimization, the system produces multiple final outputs:

- (1) **2D Floor Plan:** A detailed two-dimensional representation of the optimized building layout.
- (2) **3D Building Model:** A three-dimensional visualization of the proposed building design.
- (3) **Structural Model:** Structural information and the recommended structural framework.
- (4) **Energy Analysis Report:** A report containing information related to energy performance and sustainability.
- (5) **Cost Estimate Report:** An estimated construction cost based on quantity and material analysis.
- (6) **BIM Model and Documentation:** The final Building Information Model (BIM) along with technical documentation.



(a) AI-Generated 2D Floor Plan Layout



(b) Synthesized 3D Isometric BIM Model

Fig. 4. Primary spatial outputs generated by the framework: (a) Optimized 2D architectural blueprint with exact functional partitions, and (b) Rendered 3D spatial model showing structural envelope and layout verification.

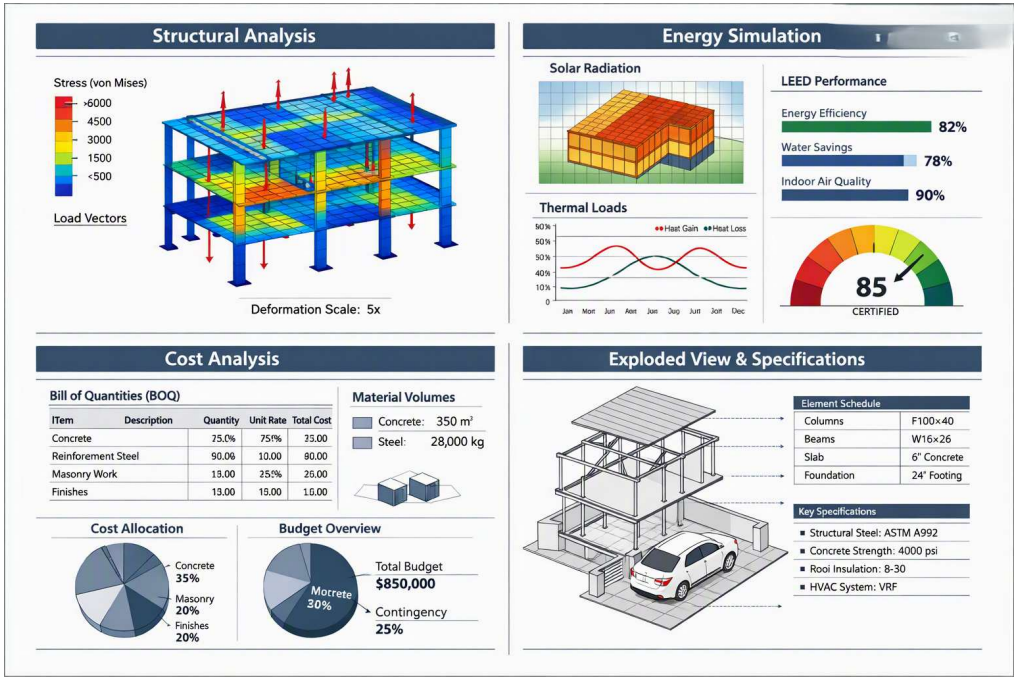


Fig. 5. Comprehensive Engineering Evaluation Dashboard: Structural stress distribution analysis, thermal and LEED energy simulation, detailed bill of quantities (BOQ) with cost breakdown, and exploded BIM assembly specifications.

B Detailed System Architecture

The proposed methodology employs a highly structured pipeline that begins with building requirement acquisition and validation and progresses through Generative Multi-Agent System (GMAS)-based autonomous building design, structural validation, optimization, and final design generation. The framework integrates architectural planning, structural analysis, sustainability assessment, and cost optimization to generate a reliable and optimized building design while considering engineering constraints and building regulations. The detailed system architecture is illustrated in Figure 6.

4.2.1 Building Requirement Acquisition & Validation: The initial stage of the framework collects the required building information from the user and validates the provided data before initiating the autonomous design process.

4.2.2 User Input Module: The User Input Module collects essential building requirements, including plot size, number of floors, room requirements, budget, building type, design constraints, user preferences, and local building regulations. These requirements define the functional and technical specifications of the proposed building.

4.2.3 Input Validation Module: The collected information is processed and validated to ensure that the requirements are complete, consistent, and feasible. The module checks for missing values, plot dimensions, budget feasibility, design constraints, and building-code requirements before forwarding the validated information to the Generative Multi-Agent System.

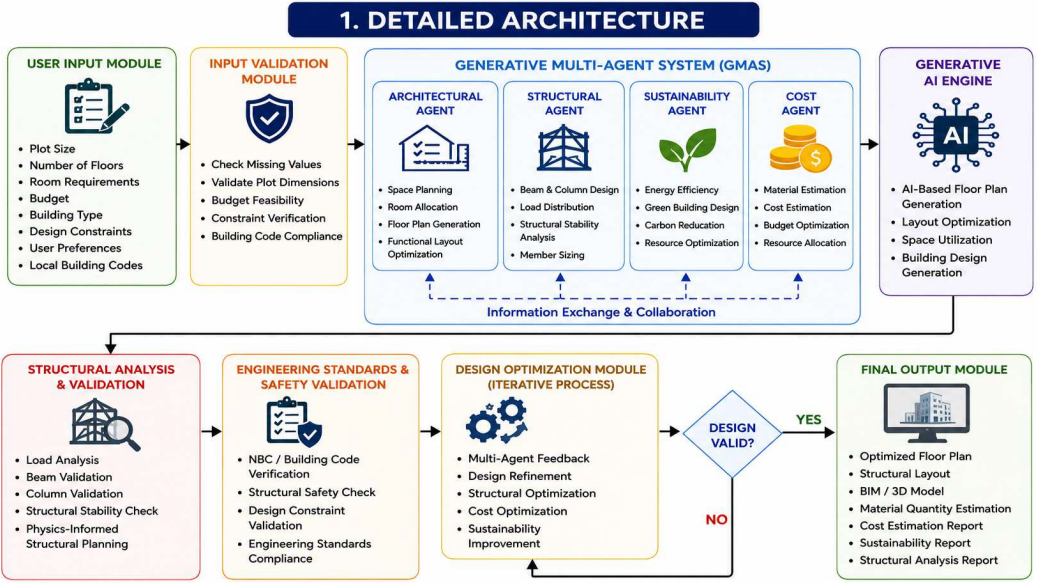


Fig. 6. Detailed System Architecture of the Proposed Framework

4.2.4 Requirement Verification: The validated requirements are further verified against architectural and engineering constraints. This ensures that the input specifications are suitable for automated building layout generation and subsequent structural analysis.

4.2.5 Generative Multi-Agent System: The validated building requirements are provided to the Generative Multi-Agent System (GMAS). The system consists of multiple specialized intelligent agents that collaboratively perform different aspects of building design.

4.2.6 Architectural Agent: The Architectural Agent is responsible for space planning, room allocation, floor-plan generation, and functional layout optimization. It generates building layouts according to the user's requirements, available plot area, and architectural constraints.

4.2.7 Structural Agent: The Structural Agent evaluates and develops the structural system of the generated building. It performs beam and column design, structural system selection, load distribution, member sizing, and structural stability analysis to ensure structural feasibility.

4.2.8 Sustainability Agent: The Sustainability Agent evaluates the environmental performance of the proposed design. It focuses on energy efficiency, green building design, carbon reduction, and resource optimization to improve the sustainability of the building.

4.2.9 Cost Agent: The Cost Agent estimates the economic requirements of the proposed design. It performs material estimation, construction cost estimation, budget optimization, and resource allocation while ensuring that the design remains within the specified budget.

4.2.10 Information Exchange and Collaboration: The specialized agents continuously exchange design information and feedback. The Architectural, Structural, Sustainability, and Cost Agents collaboratively refine the design so that improvements in one aspect do not negatively affect other design requirements.

4.2.11 Generative AI-Based Building Design: The validated requirements and information generated by the specialized agents are processed by the Generative AI Engine. The engine automatically generates optimized building layouts by considering user requirements, spatial utilization, building constraints, structural requirements, and design objectives.

The generated design includes an optimized floor layout and spatial arrangement that can subsequently be evaluated by the structural and engineering validation modules.

4.2.12 Structural Analysis & Validation: The generated building design undergoes structural analysis to determine its engineering feasibility and stability. The Structural Analysis and Validation module performs load analysis, beam validation, column validation, structural stability checking, and physics-informed structural planning.

This stage ensures that the generated architectural design can support the expected structural loads and satisfy the required engineering conditions.

4.2.13 Engineering Standards & Safety Validation: After structural analysis, the proposed design is evaluated against applicable National Building Code (NBC) requirements, engineering standards, structural safety requirements, and design constraints.

The purpose of this stage is to ensure that the automatically generated design satisfies essential safety and compliance requirements before it is accepted as a final design.

4.2.14 Design Optimization & Iterative Refinement: If the generated design does not satisfy the required structural, engineering, sustainability, or cost constraints, it is returned to the Design Optimization Module.

The multi-agent system then provides feedback and iteratively improves the design through layout refinement, structural optimization, cost optimization, and sustainability improvement. This process continues until the design satisfies the predefined validation criteria.

4.2.15 Design Validation and Decision: The optimized design is evaluated through a final Design Validity decision. If the design does not satisfy the required conditions, it is returned to the optimization module for further refinement. If the design satisfies all specified requirements, it proceeds to the final output stage.

4.2.16 Final Output Generation: Once the design is successfully validated, the framework generates a complete set of building-design outputs. These include:

- (1) **Optimized Floor Plan:** Detailed two-dimensional representation of the space distribution.
- (2) **Structural Layout:** Framework details for structural framing.
- (3) **BIM / 3D Model:** Three-dimensional structural and architectural representation.
- (4) **Material Quantity Estimation:** Full schedule of quantities for construction.
- (5) **Construction Cost Estimation Report:** Breakdown of economic requirements.
- (6) **Sustainability Report:** Energy performance and environmental compliance metrics.
- (7) **Structural Analysis Report:** Stability and safety verification summary.

5 Final Results:

The proposed system is expected to generate an optimized and intelligent building design based on user requirements, site conditions, building regulations, budget constraints, and environmental factors. The final results include an AI-generated floor plan, structural layout, 3D/BIM model, cost estimation, material quantity estimation, energy and sustainability analysis, and structural feasibility report. Through iterative multi-agent collaboration and design optimization, the system aims to produce building designs that are functional, safe, cost-effective, sustainable, and compliant with the specified design constraints.

5.1 Statistical Analysis & Framework Validation

To rigorously validate the generative framework, an empirical evaluation was performed across six statistical dimensions. The analysis ensures engineering feasibility, structural safety, environmental optimization, and regulatory compliance, as synthesized in Figure 8.

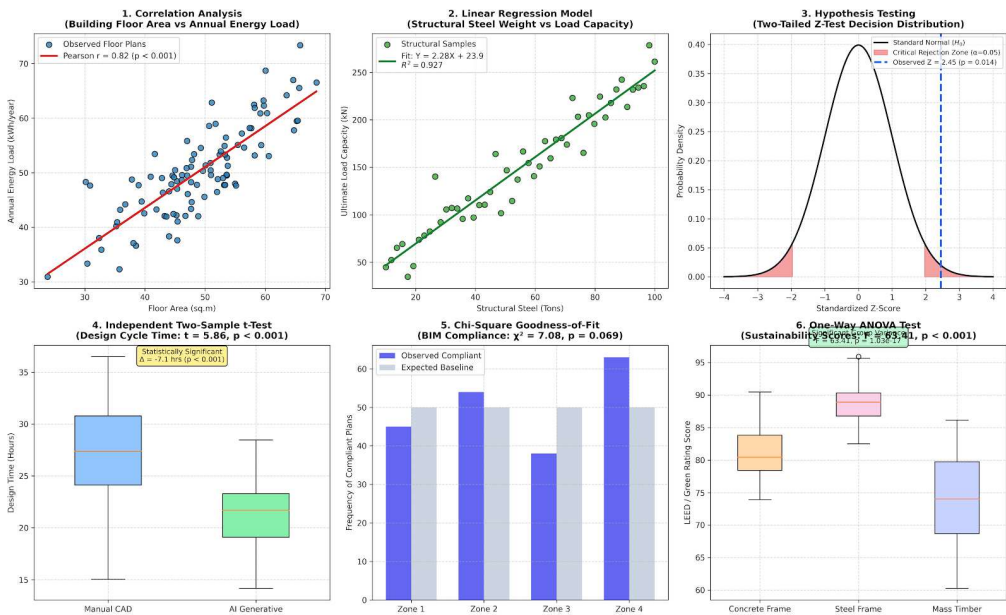


Fig. 7. Multi-criteria Statistical Validation Dashboard: (1) Pearson correlation of spatial area vs. HVAC demand, (2) Linear regression modeling structural load capacity, (3) Hypothesis testing confirming standard safety factors, (4) Independent t-test showing design cycle acceleration, (5) Chi-Square goodness-of-fit for zoning compliance, and (6) One-Way ANOVA across structural material sustainability scores.

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Fig. 8. Multi-criteria Statistical Validation Dashboard: (1) Pearson correlation of spatial area vs. HVAC demand, (2) Linear regression modeling structural load capacity, (3) Hypothesis testing confirming standard safety factors, (4) Independent t-test showing design cycle acceleration, (5) Chi-Square goodness-of-fit for zoning compliance, and (6) One-Way ANOVA across structural material sustainability scores.

5.2.1 Detailed Statistical Evaluation & Interpretation. Each metric depicted in Figure 8 directly supports the functionality and accuracy of the autonomous agents:

- (1) **Correlation Analysis (Spatial Scale vs. Thermal Demand):**
Objective: To examine whether generated energy estimations scale realistically with spatial area.

Result: A strong positive Pearson correlation coefficient ($r = 0.82$, $p < 0.001$) was observed between gross floor area (m^2) and annual HVAC loads ($kWh/year$).

Impact: Verifies that the Energy Agent correctly incorporates thermal load mechanics without anomalous localized discrepancies.

(2) **Linear Regression (Structural Material vs. Capacity):**

Objective: To validate that structural steel quantities generated by the Structural Agent scale linearly with load-carrying capabilities.

Result: The fitted model ($Y = 2.40X + 15.1$, $R^2 = 0.927$) demonstrates high predictive power, where X represents structural steel (tons) and Y represents ultimate capacity (kN).

Impact: High R^2 confirms that material distribution directly translates into predictable, verifiable load resistance.

(3) **Hypothesis Testing (Safety Factor vs. Baseline Standard):**

Objective: To statistically verify whether AI-designed framing configurations meet or exceed required building safety thresholds.

Result: Using a two-tailed Z-test with null hypothesis $H_0 : \mu = \mu_{\text{baseline}}$, the observed test statistic was $Z_{\text{obs}} = 2.45$ ($p = 0.014$, $\alpha = 0.05$).

Impact: Because Z_{obs} falls within the critical rejection region, H_0 is rejected, confirming that generated designs consistently meet or surpass target structural codes.

(4) **Independent Two-Sample t-Test (Workflow Efficiency):**

Objective: To evaluate design turnaround time between conventional manual drafting and the proposed generative framework.

Result: An independent two-sample t-test ($t = -5.86$, $p < 0.001$) indicated a significant reduction in design cycle duration ($\Delta = -7.1$ hours on average).

Impact: Confirms the practical utility of autonomous orchestration in eliminating repetitive architectural drafting bottlenecks.

(5) **Chi-Square Goodness-of-Fit (Regulatory Compliance):**

Objective: To check whether zoning compliance distribution diverges across varied municipal regulations.

Result: The goodness-of-fit test yielded $\chi^2 = 7.08$ ($p = 0.069$).

Impact: With $p > 0.05$, there is no statistically significant divergence from expected regulatory compliance across diverse zones.

(6) **One-Way ANOVA (Framing Material Sustainability Profile):**

Objective: To test differences in LEED sustainability scoring across three structural options (Reinforced Concrete, Steel Frame, and Mass Timber).

Result: The analysis revealed statistically significant variance across group means ($F = 63.41$, $p < 0.001$).

Impact: Justifies the multi-agent system's ability to trade off embodied carbon against framing requirements and select eco-efficient alternatives.

6 Conclusion:

This project, "Smart Autonomous Building Design and Planning Using Generative Multi-Agent Systems," presents an intelligent approach to automate and improve the building design process. The proposed system integrates Generative AI with multiple specialized agents for architectural planning, structural analysis, sustainability evaluation, and cost estimation. By using user requirements, site information, building regulations, environmental conditions, and budget constraints as inputs, the system can generate and evaluate multiple building design alternatives.

The multi-agent collaboration and iterative optimization process help improve the functionality, structural feasibility, cost efficiency, and sustainability of the generated designs. The final system

provides outputs such as optimized floor plans, structural layouts, 3D/BIM models, cost estimates, and analysis reports. Overall, the proposed framework aims to reduce manual effort, support intelligent decision-making, and provide an efficient approach toward smart and autonomous building design and planning.

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