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A Study on the Development of an Artificial Intelligence-Based Architectural Agent for Schematic Design Concept Using GPT-4 Language Models and Case-Based Reasoning

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Abstract This study introduces the "Design Competition Concept Proposal AI Agent," designed to reduce cognitive load and enhance creativity in schematic design. In public competitions, architects often face information overload when interpreting briefs with legal, technical, and programmatic constraints. To address this, the system integrates GPT-4-based Large Language Models (LLMs) with Case-Based Reasoning (CBR) through a retrieve–reuse–revise framework. The process involves structuring brief information, extracting keywords across five categories—sense of place, program, functionality, sustainability, and publicness—and generating three differentiated concepts guided by spatial, environmental/technical, and socio-cultural strategies. Applied to five public projects, the system produced consistent keywords and diverse concepts, with expert reviews confirming reduced processing time and improved conceptual diversity. These findings highlight the potential of LLM–CBR integration to automate conceptual reasoning and support structured human–AI collaboration in early design.

Keywords: Schematic Design, Design Concept, GPT-4, LLM, Case-Based Reasoning, Public Architectural Design Competitions, Cognitive Load

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1. Introduction

1.1. Background of the Study

The schematic design phase is pivotal in defining the direction and identity of a project, particularly in public competitions where the concept reflects both creativity and strategy. As Rittel and Webber (1973) and Simon (1973) note, this process is non-linear, with problems and solutions evolving together.

Designers must interpret complex briefs that integrate legal, technical, and contextual factors, often leading to cognitive overload and fixation that hinder creativity. To address this, the study introduces the Design Competition Concept Proposal AI Agent, combining GPT-4's language capabilities with Case-Based Reasoning (CBR). The system seeks to reduce cognitive load while improving consistency and creativity.

The framework is structured into two phases**:** Inter−pretation, which analyzes and organizes the brief, and Ideation, which generates concepts based on the analysis. Within this process, the AI agent supports designers by reinforcing both analytical clarity and creative exploration.

This framework defines where and how the AI agent supports the designer's thought process (Fig. 1).

2. Theoretical and Technical Background

2.1. Cognitive Science Approach to Concept Derivation in Design

In schematic design, the concept is not merely a functional or formal output but a cognitive construct that incorporates values such as symbolism, publicness, sense of place, and sustainability. This dimension is particularly critical in public architecture, where conceptual depth shapes both design direction and evaluative competitiveness.

Concept generation relies on abductive reasoning, a non-deterministic process of forming plausible ideas under incomplete information (Gero & Roozenburg, 1997). While this reasoning, closely linked to schema-based thinking, enables rapid interpretation of complex requirements, it also imposes a heavy cognitive burden by requiring simultaneous analysis and creativity.

To address these challenges, this study proposes an AI-assisted concept reasoning system that integrates Case-Based Reasoning (CBR) to emulate experience-driven logic, GPT-4 Large Language Models (LLMs) to support

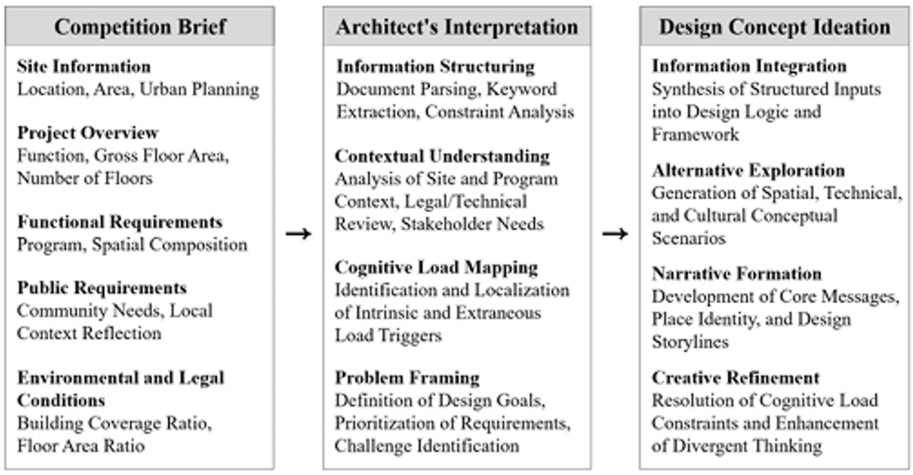


Figure 1. Design Conceptualization Process in Public Architectural Competitions.

abductive and generative reasoning, and semantic embedding models such as Word2Vec and Sentence-BERT to ensure conceptual diversity. In this framework, CBR retrieves and adapts prior cases, GPT-4 expands them with novel concepts, and semantic embeddings evaluate similarity to prevent fixation and redundancy.

Whereas recent studies on LLMs have focused on BIM generation, drawing automation, or design queries (Jang & Lee, 2024; Du et al., 2024), the present study structurally integrates CBR, LLMs, and semantic control to support early-stage ideation. By embedding similarity thresholds, the system enhances both diversity and conceptual clarity, contributing to the advancement of AI-assisted design cognition.

2.2. AI-Based Strategy for Design Concept Derivation

The schematic design phase requires integrating information interpretation, creativity, and strategic reasoning, but rigid schema-driven thinking often constrains this process. To overcome such limits, a support system is needed to complement designers' cognition and foster conceptual diversity.

An AI-based approach can lessen cognitive burden by structuring unstructured briefs. Combining natural language processing with case-based reasoning enables systematic interpretation and creative pathways for concept development.

This study therefore proposes an AI-assisted framework that guides designers through information structuring, keyword refinement, and concept diversification. Detailed methods and algorithms are presented in Chapter 3.

3. System Structure and Processing Process

3.1. Theoretical Foundation for System Design

To support conceptual thinking in public design competitions, the proposed Design Competition Concept Proposal AI Agent integrates cognitive theories with AI technologies. It translates reasoning processes into modules aligned with three models: abductive reasoning for concept generation, schema-based thinking for keyword structuring, and cognitive load theory for information reduction.

These theories map to system components: a Concept Scenario Generator, Keyword Classifier, and Brief Structuring Module. The system processes unstructured briefs through three steps: (1) automated interpretation of project and site data, (2) keyword extraction and categorization with Sentence-BERT, and (3) scenario generation along spatial, environmental/technical, and socio-cultural axes, with cosine similarity control ensuring diversity.

This architecture converts intuitive ideation into a structured flow—analysis, classification, and generation—enhancing both reasoning support and conceptual diversity.

The overall structure of the system consists of four major steps: (Fig. 2)

3.2. Detailed Processing Flow

This section describes the processing steps of the Design Competition Concept Proposal AI Agent, which operates sequentially through document input, information extraction, semantic refinement, concept generation, and final output. The process begins with the upload and preprocessing of design briefs in PDF or Word format. The parser analyzes both structural and semantic components—such as headings, body text, and tables—and converts them into a machine-readable format suitable for contextual analysis by GPT-based models.

The second stage focuses on the extraction of essential information. Guided by predefined prompts, GPT-4 identifies and organizes data such as the project overview, client, site conditions, programmatic requirements, spatial composition, and technical or legal constraints. This information is structured into JSON, providing a coherent foundation for concept development.

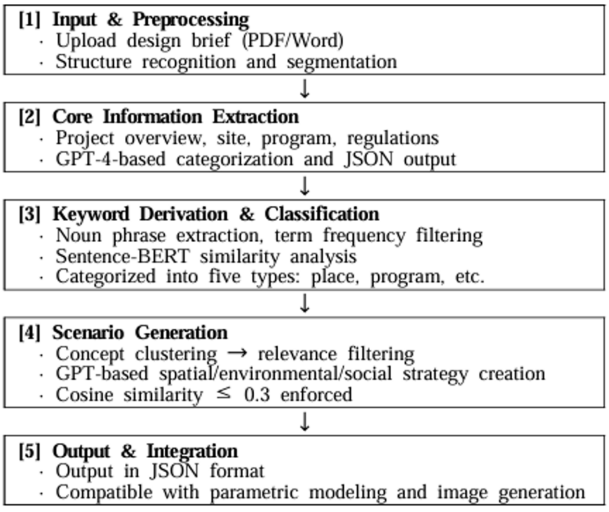


Figure 2. Summary of Processing Steps in the Design Concept Proposal AI Agent.

The next stage refines keywords from the GPT output. Generic or low-relevance terms are filtered out, while Sentence-BERT embeddings are used to group semantically related words and eliminate redundancy through cosine similarity analysis. The finalized keywords are categorized into five cognitive dimensions of design thinking: sense of place, program relevance, functionality, environmental sustainability, and publicness.

In the final stage, GPT-4 synthesizes these categorized keywords into concept scenarios. Each scenario is generated along one of three strategic axes—spatial configuration, environmental/technical strategy, or socio-cultural context—and articulated into a concise design statement. Sentence-BERT similarity scores are applied to ensure that scenarios remain independent, with only those at or below 0.3 retained.

By integrating the cyclical logic of Case-Based Reasoning (Retrieve, Reuse, Revise) with GPT-4's generative capacity, the system transforms intuitive ideation into a structured process. This structured flow of analysis, classification, and generation supports designers by reducing cognitive burden while fostering conceptual clarity, diversity, and creativity in early-stage design.

3.3. Output Structure and Integration Potential

The system generates its final design concepts in a structured JSON format, ensuring consistent organization and facilitating integration with downstream tools. Each scenario consists of core keywords, a functional statement, a strategic approach, and spatial implications, expressed in concise narrative form and annotated with metadata such as concept type, strategy axis, and timestamp. This structured format not only clarifies representation but also enables interoperability with diverse computational applications.

The output supports several modes of integration. For automated design tools, the JSON data incorporates sufficient spatial and functional logic to inform rule-based layout generators or custom visualization systems. It also provides inputs for image-generation modules, where keywords and strategy statements can serve as prompts for diffusion-based models, allowing intuitive visual exploration.

Furthermore, the JSON structure streamlines document automation by generating summaries, proposal drafts, or comparative charts, thereby improving communication with stakeholders and enhancing workflow efficiency. By translating design reasoning into structured and reusable data, the system creates a foundation for advanced applications such as parametric modeling, simulation-based design, and architectural visualization, reinforcing both rigor and adaptability in early-stage design.

4. System Application and Empirical Analysis

This section presents the experimental framework and target projects used to evaluate the applicability and effectiveness of the proposed system. The main objective was to test whether the AI-based approach could interpret unstructured design briefs from public architectural competitions and autonomously generate design concepts that are both valid and strategically diverse.

Five real-world competition projects were selected as test cases. For each, the system carried out document parsing, core information extraction, keyword refinement, and concept scenario generation. The outputs were examined qualitatively to assess plausibility and design relevance, while expert reviews further evaluated their practical utility. In parallel, a quantitative analysis of semantic similarity verified that the generated concepts maintained strategic diversity and semantic independence.

The projects represented small- to medium-scale public buildings, ranging from 1,900 to 5,000 square meters, including administrative welfare centers, community facilities, and training centers. This range ensured that the system was tested under varied design conditions, providing a robust basis for evaluating both performance and generalizability (Table 1).

Although the uses and scales were similar, each project had distinct design conditions—site constraints, program compositions, and document structures—providing a robust testing environment for verifying the system's repeatability and generalizability. Using the same process across all cases, the system generated a total of 15 concept scenarios, which are analyzed both quantitatively and qualitatively in the next section.

4.2. Application Method and Execution Procedure

This section presents the experimental procedure used to apply the proposed Design Concept Proposal System to public architectural design briefs. The goal was to test

Table 1. List of Target Projects for Empirical Evaluation

No.	Project Name	Primary Use	Gross Floor Area	Floors	Year
1	Sinwol 1-dong Community Center	Public Admin Facility	~4,900 m^2	B2F–4F	2023
2	Donam 1-dong Government Complex	Integrated Admin Office	~1,920 m^2	B1F–6F	2023
3	Red Cross Southern Volunteer Center	Volunteer Training Center	~2,000 m^2	B1F–4F	2024
4	Chungnam Leadership Training Center	Command & Training Facility	~2,970 m^2	2F	2024
5	Maetan 1-dong Administrative Welfare Center	Public Admin Facility	~2,850 m^2	—	2024

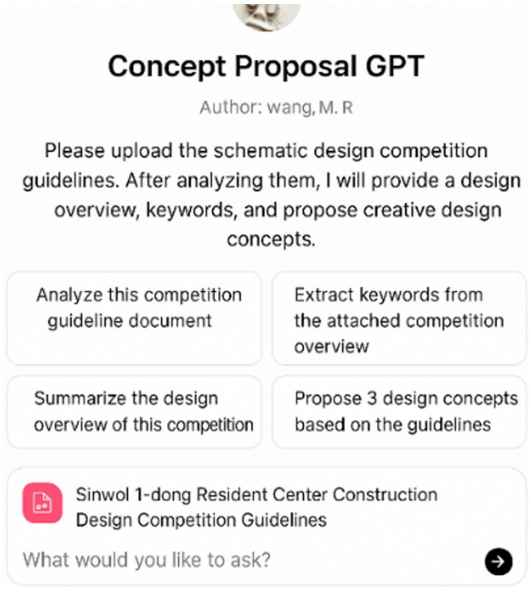


Figure 3. Screenshot of the Upload Interface of the Concept Proposal AI Agent

the system's ability to autonomously process complex information and generate coherent, diverse concepts without manual designer input.

The procedure comprised four stages: document preprocessing, core information extraction, keyword refinement, and concept scenario generation, each following the protocol described in Chapter 3. To verify reliability, a repetition test was conducted using the same brief multiple times, and the outputs were quantitatively examined through cosine similarity and conceptual axis differentiation to confirm semantic independence and strategic diversity.

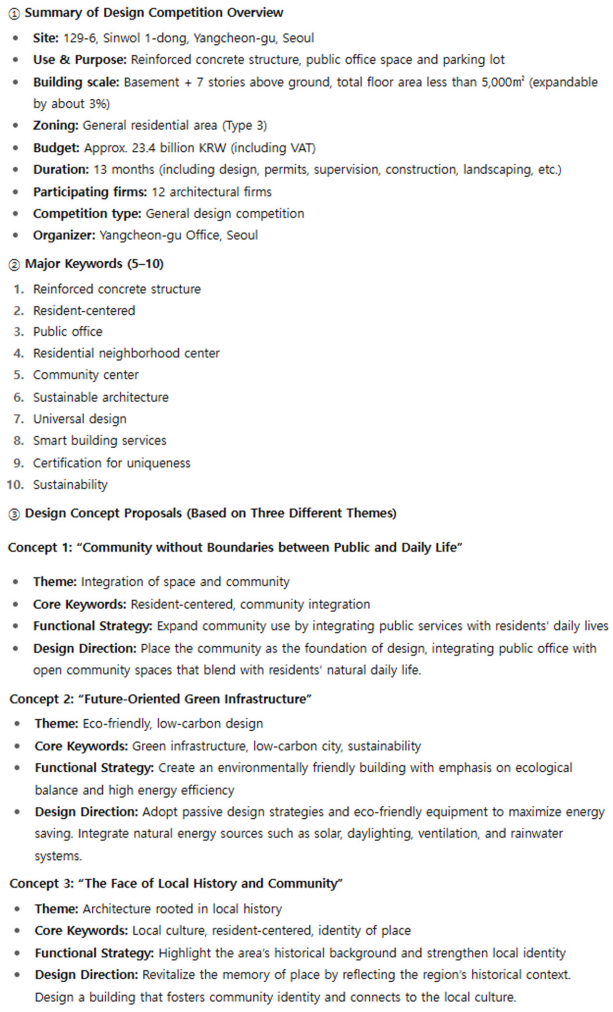
4.3. System Output and Analysis

The system was applied to five public design competition projects, and in each case the extracted keywords and generated concept scenarios reflected the specific characteristics of the design briefs. On average, 9.2 keywords were automatically derived per project (range: 8-11). The scenarios were organized along three strategic axes: spatial configuration, environmental or technical strategy, and regional or social strategy. Each was composed of 3-5 keywords and expressed in a concise short-paragraph format. Although the projects were similar in scale and use, the resulting concepts captured distinct programmatic requirements, site conditions, and document structures, demonstrating the system's adaptability to context.

For instance, in the Sinwol 1-dong Community Center brief, the requirement for "green building and zero-energy certification" was identified as a core keyword and developed into the concept *"Zero+ future-oriented administrative*

Table 2. Summary of Keywords and Design Concepts per Case

Case	Main Keywords	Concept 1 (Spatial Strategy)	Concept 2 (Technical/Environmental)	Concept 3 (Social/Cultural)
Sinwol 1-dong	Complex office, citizen convenience, zero energy, green building, locality	Community belt with shared boundaries	Zero+ future-oriented admin infrastructure	Place of memory, neighborhood identity
Donam 1-dong	Relocation, urban renewal, barrier-free, zero energy, local governance	Compact synergy	Zero-energy civic hub	Open plaza for communication
Red Cross Center	Integration, disaster response, symbolism, training facility	Volunteer engine, functional harmony	Platform for recovery and response	City façade of volunteers
Chungnam Center	Command system, training scenario, knowledge sharing, zero energy	One mission, unified space	Zero-base camp	Stage for civic scenarios
Maetan 1-dong	Community interaction, park linkage, energy efficiency, modular space	Borderless neighborhood facility	Breathing public architecture	Dual-faced civic center



① **Summary of Design Competition Overview**

- **Site:** 129-6, Sinwol 1-dong, Yangcheon-gu, Seoul
- **Use & Purpose:** Reinforced concrete structure, public office space and parking lot
- **Building scale:** Basement + 7 stories above ground, total floor area less than 5,000m² (expandable by about 3%)
- **Zoning:** General residential area (Type 3)
- **Budget:** Approx. 23.4 billion KRW (including VAT)
- **Duration:** 13 months (including design, permits, supervision, construction, landscaping, etc.)
- **Participating firms:** 12 architectural firms
- **Competition type:** General design competition
- **Organizer:** Yangcheon-gu Office, Seoul

② **Major Keywords (5–10)**

1. Reinforced concrete structure
2. Resident-centered
3. Public office
4. Residential neighborhood center
5. Community center
6. Sustainable architecture
7. Universal design
8. Smart building services
9. Certification for uniqueness
10. Sustainability

③ **Design Concept Proposals (Based on Three Different Themes)**

Concept 1: "Community without Boundaries between Public and Daily Life"

- **Theme:** Integration of space and community
- **Core Keywords:** Resident-centered, community integration
- **Functional Strategy:** Expand community use by integrating public services with residents' daily lives
- **Design Direction:** Place the community as the foundation of design, integrating public office with open community spaces that blend with residents' natural daily life.

Concept 2: "Future-Oriented Green Infrastructure"

- **Theme:** Eco-friendly, low-carbon design
- **Core Keywords:** Green infrastructure, low-carbon city, sustainability
- **Functional Strategy:** Create an environmentally friendly building with emphasis on ecological balance and high energy efficiency
- **Design Direction:** Adopt passive design strategies and eco-friendly equipment to maximize energy saving. Integrate natural energy sources such as solar, daylighting, ventilation, and rainwater systems.

Concept 3: "The Face of Local History and Community"

- **Theme:** Architecture rooted in local history
- **Core Keywords:** Local culture, resident-centered, identity of place
- **Functional Strategy:** Highlight the area's historical background and strengthen local identity
- **Design Direction:** Revitalize the memory of place by reflecting the region's historical context. Design a building that fosters community identity and connects to the local culture.

Figure 4. Screenshot of AI Agent Output. (Sinwol 1-dong Comunity Center)

infrastructure." Likewise, in the Maetan 1-dong project, conditions such as "park linkage" and "flexible space" informed the concept *"Breathing public architecture."* These examples illustrate the system's ability to interpret embedded requirements and restructure them into strategic design concepts.

A summary of keywords and concept scenarios is presented in Table 2:

This evidences the system's ability to semantically interpret unstructured expressions and construct logically coherent concepts (Fig. 4).

These cases suggest that the generated design concepts are not mere linguistic combinations, but cognitive interpretations of the brief's embedded intentions—demonstrating the system's semantic reasoning capabilities.

To quantitatively verify the semantic independence and strategic distinctiveness of the generated concepts, a cosine similarity analysis was conducted. Each concept scenario was embedded using Sentence-BERT and categorized by conceptual axis (spatial, technical, social). Cosine similarity scores between concept pairs were calculated as follows:

Project Name	C1–C2	C1–C3	C2–C3	Note
Sinwol	0.27	0.25	0.19	All values ≤ 0.3
Donam	0.24	0.27	0.20	〃
Red Cross	0.26	0.28	0.22	〃
Chungnam	0.23	0.29	0.20	〃
Maetan	0.28	0.26	0.20	〃

Average Cosine Similarity = 0.243

To assess output stability under identical input conditions, the Sinwol 1-dong brief was processed five times. The extracted keywords from each run were compared against the baseline set from the first run. As summarized in Table Y, the system consistently reproduced the same or nearly identical keywords. The consistency rate across repeated trials ranged from 90% to 100%, resulting in an average of 92.5%. This outcome confirms that the system reliably interprets the same input document and generates stable design concept scenarios, thereby validating the repeatability of the proposed concept reasoning framework.

Run	Keywords	Matches with Baseline	Consistency Rate
1	(Baseline keywords)	—	—
2	Minor variation in last keyword	9 / 10	90.0%
3	Identical to baseline	10 / 10	100.0%
4	Minor variation	9 / 10	90.0%
5	Minor variation	9 / 10	90.0%

The repetition test yielded an average consistency rate of 92.5%, indicating that the system reliably interpreted the same input document across multiple runs. This high level of stability demonstrates that the generated design concepts are not random variations but consistent outcomes of the reasoning process. Accordingly, the results validate both the reliability and the repeatability of the proposed concept generation framework.

5. Conclusion

This study proposed and validated a design concept proposal system that integrates GPT-4-based Large Language Models (LLMs), Case-Based Reasoning (CBR), and Sentence-BERT semantic embedding. Designed to address cognitive challenges in public architectural competitions—such as information overload, interpretive inconsistency, and conceptual fixation—the framework, grounded in abductive reasoning, schema-based thinking, and cognitive load theory, automatically interprets unstructured briefs, extracts essential information, and

generates diversified concept scenarios. Applied to five real-world competition projects, the system consistently produced semantically distinct and contextually relevant concepts. Quantitative analysis confirmed strategic diversity (average cosine similarity of 0.243), while repetition testing verified output stability (92.5% consistency). These results highlight the system's ability to reduce interpretation time, enhance conceptual diversity, and provide structured outputs for integration into design workflows.

Nonetheless, the study has limitations. The scope was confined to five medium-scale public buildings, limiting generalizability across project types and scales. Evaluation relied mainly on semantic similarity and expert review, without validation through participatory design workshops. Moreover, the system was applied only to the schematic phase, leaving subsequent design stages untested.

Future research should expand the case base to include larger and more complex projects, as well as diverse cultural and regulatory contexts. Participatory workshops would allow assessment of user acceptance and practical utility. Further integration with parametric modeling, simulation, and collaborative platforms may extend applicability beyond early-stage ideation, enabling continuous AI-assisted support throughout the design process.

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