PhD Thesis Topic 2

Reflexive Human–AI Co-design for Iterative Building Design

Progressive constraint elicitation, simulation and decision support

Context and objective

Architectural design involves iterative trade-offs between spatial quality, architectural intent, cost, environmental impact, comfort, technical performance and regulatory requirements. Many criteria remain implicit or emerge through exploration: problem formulation and solution development evolve together (Dorst & Cross, 2001; Gero & Kannengiesser, 2004). Simulation-based optimisation supports performance-driven exploration (Nguyen et al., 2014), but the progressive formulation of constraints remains a central challenge.

Within the MIAI ARCHIMED framework, this PhD will investigate how AI can shorten the design–performance-validation cycle by helping architects understand consequences and explore alternatives during conception. The architect retains the overall vision, including aesthetic, spatial and contextual intentions; AI assists with selected explicit criteria and progressively clarified requirements. Computational checks will support, rather than replace, professional engineering and regulatory validation.

The approach adapts a reflexive architecture from understanding inhabited practices to exploring emerging building designs. Its hypothesis is that a system combining project-specific knowledge, simulation, selective questioning and generative computation can improve both problem formulation and solution exploration. It will expose uncertainties and trade-offs while preserving the architect's decision-making authority, consistent with human–AI interaction principles (Amershi et al., 2019).

Proposed plan

Five interconnected components will support a conversational and visual decision-support environment:

1. **Design State Model.** An evolving representation will combine geometry, materials, technical systems, site conditions, occupancy, performance targets, regulations, budget, architectural intentions, hard constraints and preferences. It will distinguish measured, supplied, regulatory, simulated, inferred, analogy-based, assumed and generated information, recording uncertainty, unresolved questions and decision history.
2. **Building System Simulator.** Physical models will evaluate the current design and alternatives. Measurements will support calibration in retrofit projects (Coakley et al., 2014); explicit assumptions and analogous cases will support new-building studies. Simulation experiments will investigate how design variables affect performance.
3. **Reflexive Design System.** "Revealators" will translate simulation, sensitivity and uncertainty analyses into intelligible observations (Tian, 2013). They may expose conflicting requirements or reveal that overheating estimates depend on an unspecified occupancy schedule. Their significance remains for the architect to assess.

4. **Design Annotation Helper.** Natural language, comments and sketch-related annotations will progressively capture informal intentions. An LLM will propose structured interpretations for architect confirmation and correction. Selective questioning, informed by active learning (Settles, 2009), will target useful missing information while limiting unnecessary interruptions.
5. **Hybrid Generative Solver.** An LLM will orchestrate specialised constraint solvers, parametric generators, optimisation and simulation tools, following the tool-based integration explored by Makatura et al. (2024). It will generate diverse alternatives, verify computable constraints and identify information needed to distinguish solutions. Numerical feasibility will rely on explicit computational checks.

Project-specific knowledge and iterative loop

The research will compare ways of adapting a general-purpose LLM to an architectural project: retrieval-augmented generation (RAG) over the brief and applicable planning documents; knowledge-graph-assisted retrieval (GraphRAG); and orchestration of simulation experiments. Retrieved passages and computational outputs will be linked to their sources and assumptions. Regulatory interpretations and inferred constraints will remain distinguishable from confirmed project requirements.

The iterative loop will follow this sequence: architect input → Design State Model → Building System Simulator → Reflexive Design System and revealators → Hybrid Generative Solver → visualisation and architect decision → revised annotations and constraints. Generation and simulation may cycle internally before presenting alternatives. Each iteration will explore both feasible designs and the missing information most likely to improve subsequent decisions.

Existing buildings will supply measured performance, configurations and analogous cases, drawing on case-based reasoning (Maher et al., 1995). Invented buildings will constitute hypothetical alternatives checked against current constraints. Generic knowledge, evidence from analogous buildings and project-specific simulation will remain distinct: a retrieved precedent is a starting point, not proof of performance for the current project.

Research questions

The central question is: How can human–AI co-design progressively construct an architectural problem and its solutions while reducing design–validation iterations and preserving architectural agency?

- **RQ1:** How can an evolving Design State Model represent heterogeneous intentions, constraints, uncertainty and information provenance?
- **RQ2:** How can revealators expose meaningful sensitivities, conflicts and opportunities without imposing architectural preferences?
- **RQ3:** How can dialogue and project-grounded retrieval transform informal intentions and documentary requirements into traceable, computable constraints?
- **RQ4:** How can LLM orchestration, knowledge graphs, constraint solving and physical simulation generate diverse alternatives with verifiable performance?
- **RQ5:** How can uncertainty, sensitivity analysis, simulation experiments and analogy identify the information most useful for the next iteration?

Methodology, validation and contributions

The work will formalise the design-state representation and interaction protocol, implement the hybrid architecture, and evaluate alternative retrieval and tool-orchestration strategies. It will build on a prototypes for reflexive reasoning, annotation and generation, and investigate reuse of BATEM's building simulator and BATERM's declarative, iterative model-design approach.

Two demonstrators will address retrofit, using measurements for calibration, and early-stage new-building design, with deliberately incomplete information. Comparative studies will involve realistic tasks with and without the system; component ablations will distinguish the effects of retrieval, revealators and selective questioning. Evaluation will measure constraint satisfaction, performance uncertainty, alternative diversity, question relevance, traceability, architect workload and agency, and the number of revisions needed to reach the selected performance targets. Fewer iterations will be assessed alongside design quality and exploration breadth.

The initial scope will cover thermal and energy performance, comfort, geometric and spatial constraints, and one environmental or economic criterion. Expected contributions are an evolving design-state model; architectural revealators; a project-grounded method for constraint elicitation and information acquisition; and a validated hybrid decision-support architecture. The guiding principle is: the system reveals, explores and checks; the architect decides.

Hosting environment

The PhD is part of the scientific programme of the ARCHIMED Chair – ARCHItectural Multi-criteria Exploration & Design, funded by the MIAI Cluster within the France 2030 programme (ANR-23-IACL-0006). ARCHIMED aims to develop architectural design-assistance methods combining artificial intelligence, multi-criteria evaluation and human–AI co-design, with particular attention to the early stages of the project, when choices concerning form and performance remain open.

Candidate profile and desired skills

Applicants should hold a Master's degree, an engineering degree, or an equivalent qualification in computer science/AI, applied mathematics, engineering sciences, computational design, or a related field. Candidates with a background in architecture may also be considered if they have strong skills in programming and machine learning.

Particularly valued skills

- Python programming and experience with a deep-learning environment;
- knowledge of machine-learning methods, building physics and optimization;
- ability to work in an interdisciplinary context, scientific autonomy, and ability to write in English.

Practical information

- **Type of contract:** 36-month doctoral contract.
- **Expected start date:** January 2027.
- **Salary:** according to the statutory salary scale applicable to doctoral contracts.

Application

- The application file must include:
- CV
- cover letter
- academic transcripts (Master's and Bachelor's)
- Master's thesis or an equivalent document enabling assessment of the candidate's previous work
- copies of diplomas

Deadline for applications: 15 November 2026.
Shortlisted candidates will be interviewed on: 18 November 2026.

Applications must be sent to:

bensaci.a@grenoble.archi.fr

With a copy to:

patrick.reignier@univ-grenoble-alpes.fr

stephane.ploix@grenoble-inp.fr

***Suggested subject line**: "Application PhD Thesis 2 ARCHIMED _ LAST NAME First name".*

References

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