

Domain-Specific Libraries as Focus Lenses for AI-Assisted Architectural Writing and Education

A Method for Structuring LLM-Based Design Workflows

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Abstract. *Large language models (LLMs) such as ChatGPT are rapidly becoming default instruments for writing, research, and communication in architectural education. Their fluency, however, is grounded in statistical generality and tends toward a homogenized common sense: correct but generic texts, reduced disciplinary specificity, and a weakening of architectural voice and authorship. This paper argues that architectural education requires complementary, domain-specific infrastructures to situate and guide the use of LLMs, understanding computation as a form of literacy rather than a problem-solving tool alone. It presents a reproducible method for constructing and operating domain-specific libraries as focus lenses: LLMs are employed as linguistic and connective engines, while curated libraries condition, direct, and enrich their outputs toward disciplinary specificity. The method is demonstrated through two cases: the multimodal cascade of '1001 in 1', a scenographic project using LLM prompt chains seeded with curated corpora to generate coherent architectural compositions at scale - developed with Agostino Nickl and Adil Bokhari; and a design-build studio in which students applied the same logic of curated worlds and AI-supported narrative development to design and construct built pavilions - developed with Clemens Plank. The paper concludes by proposing domain-specific libraries as instruments of architectural authorship, expression, and thinking in the age of AI.*

Keywords. *computational design theory, architectural education, AI-assisted writing, domain-specific knowledge, digital libraries, large language models.*

INTRODUCTION: THE PROBLEM OF GENERIC INTELLIGENCE

Large language models are becoming default tools for writing, research, and ideation in architecture. They are powerful because they offer fluency, speed, and an extraordinary connective capacity: the ability to link any concept to any other, across domains, at the speed of a query. In architectural education, they promise to accelerate

research, help students articulate design positions, and facilitate the kind of cross-referential thinking that architectural discourse has always valued. Yet these same capabilities carry a disciplinary risk. LLMs operate through pattern completion and statistical association (Brown et al., 2020; Kampelopoulos et al., 2025). Their outputs tend toward what might be called generic plausibility: a kind of statistically averaged common sense that sounds correct but

carries little disciplinary weight. When students use ChatGPT to write about architecture, the result is often fluent but weakly positioned. The language is smooth where architecture demands rough edges, producing off-the-shelf, commonsensical, and fashionable arguments. This paper argues that the disciplinary issue is not whether AI is useful in architecture, but how architectural specificity can be maintained when working with systems designed for generality (Carpo, 2017). The question is not one of prohibition or celebration, but of infrastructure: what kinds of knowledge environments can redirect the general-purpose power of LLMs toward architecturally situated objects? The central thesis is that domain-specific libraries and custom search environments can act as focus lenses that redirect LLM output toward disciplinary specificity. Rather than only relying on the LLM's own training data, which reflects the statistical average of the internet, the library introduces curated, intentionally partial, and disciplinarily dense material that conditions the LLM's field of articulation. Through such infrastructures, AI-assisted writing becomes not a shortcut to generic text, but an architectural practice of selection, positioning, and composition. This paper contributes: (1) a method for constructing and operating domain-specific libraries as focus lenses for AI-assisted architectural writing; (2) a conceptual framework positioning such libraries as instruments for disciplinary specificity; and (3) two applied demonstrations—a multimodal experiment ('1001 in 1') and a design-build studio—showing how the method operates in practice.

BACKGROUND AND CONCEPTUAL POSITION

LLMs as Common Sense Machines

LLMs are not neutral knowledge engines. Trained on vast internet corpora, they encode the statistical distribution of language across billions of documents (Vaswani et al., 2017; Brown et al., 2020). This gives them a remarkable capacity for linguistic connection,

but their outputs reflect what is most probable given prior language, not what is most valuable given a particular disciplinary context. In architecture, where design intelligence is deeply tied to cultural, material, and theoretical specificity (Del Campo, 2022), an LLM can generate text about the relationship between light and structure, but it will tend to produce the most common version of that relationship rather than the most interesting, contested, or specific one. This characteristic has been described as a form of computational common sense (Nickl, Bokhari and Roman, 2024): the LLM functions as a universal connector, but the connections it produces are weighted toward the generic.

Computation as Literacy

The conceptual foundation for this paper draws on the understanding of computation as a form of literacy rather than merely a tool for optimization or automation. Bühlmann, Hovestadt, and Moosavi (2015) have argued that coding, searching, querying, and computing are modes of articulation in their own right. Papert (1980) established that computational environments are epistemological frameworks that shape how learners construct knowledge. If computation is literacy, then the way one structures queries, builds search environments, curates databases, and orchestrates prompt sequences is itself an architectural act (Picon, 2010). Prompting is not a neutral instruction; it is a compositional decision. Curating a library is the design of a knowledge environment that shapes what can be found, connected, and said.

Domain-Specific Libraries as Epistemic Instruments

A domain-specific library, as used here, is not merely a collection of texts. It is a designed knowledge environment: curated, intentionally biased, disciplinarily dense, and selective rather than universal. The library exists within a constellation of actors: LLMs, image generators, search engines, data repositories, orchestration platforms, and human

composers, each with specific capacities. The library's role within this constellation is to act as a focus lens (Figure 1): it does not produce output directly, but redirects the outputs of other actors toward disciplinary specificity. When such a library is coupled with a search engine that operates on contextual proximity rather than keyword matching alone, it becomes an epistemic instrument: a way of producing possible relations between ideas, authors, and positions that would not emerge from a generic search. This is consistent with contemporary work on retrieval-augmented generation (RAG), where external knowledge bases ground and redirect LLM outputs (Lewis et al., 2020; Gao et al., 2024). However, the emphasis here is not on factual accuracy but on disciplinary orientation: the library introduces a specific intellectual world that the LLM navigates, while orchestration platforms such as Wolfram Mathematica bind the constellation together, routing queries through libraries, feeding fragments

to LLMs, and chaining outputs across media.

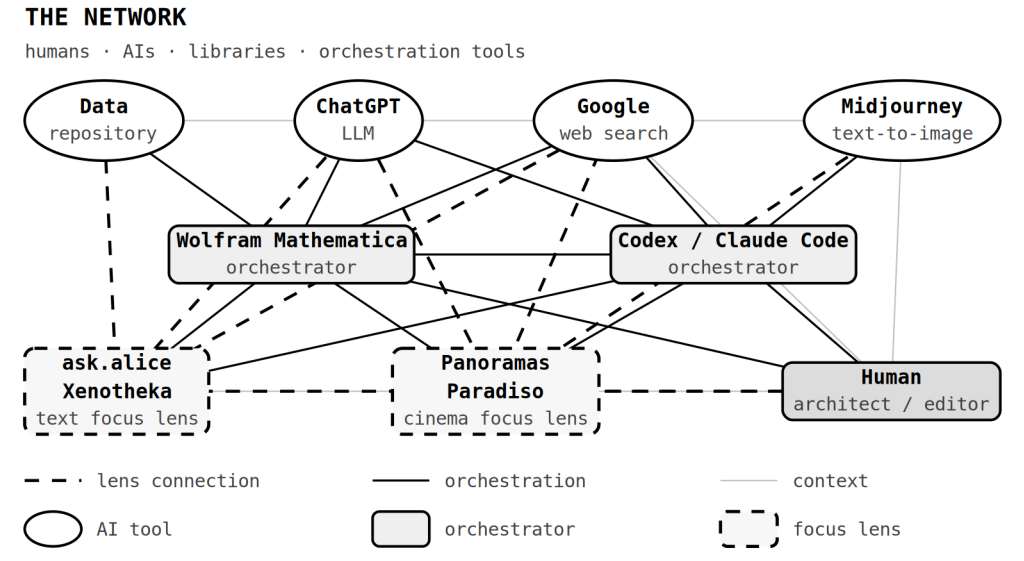
METHOD: DOMAIN-SPECIFIC LIBRARIES AS FOCUS LENSES

This section describes the proposed method for constructing and operating domain-specific libraries as focus lenses in AI-assisted architectural workflows. Rather than relying on direct interaction with general-purpose LLMs, the method introduces a structured constellation of curated corpora, custom retrieval systems, and orchestration environments that condition and redirect generative processes.

The Problem with Direct LLM Use

The default workflow in AI-assisted writing is straightforward: a user poses a question, and the LLM responds with text drawn from its training data. In architectural contexts, the result is typically fluent but broadly generic. Architectural vocabulary may appear, but without

Figure 1
The constellation of actors in AI-assisted architectural writing. Each node carries a distinct capacity: LLMs generate, libraries focus, orchestrators bind, image generators visualize, and humans compose.



the lineage, specificity, or tension that distinguishes positioned writing from summary. For education, this creates a particular challenge: students who rely on direct LLM interaction receive text that sounds competent but lacks the intellectual work of positioning—choosing between references, navigating conflicting theoretical traditions, and developing a voice within and against a discourse. The risk is not plagiarism in the narrow sense, but a subtler erosion of the compositional practices that define architectural literacy.

The Role of the Library

The proposed method introduces the domain-specific library as a mediating layer between the user and the LLM. The library is defined by four properties: it is curated (assembled through deliberate selection), intentionally biased (organized around a particular disciplinary perspective), selective rather than universal (it excludes as much as it includes), and disciplinarily dense (its contents carry specific intellectual weight within the field). Two concrete instances serve as examples. First, Xenotheke (Roman, 2018) is a curated digital library of architectural, theoretical, and philosophical texts. Second, Paradiso (Orozco, 2019) is a curated database of cinematic references organized around visual, atmospheric, and directorial qualities. Both are private, partial, and designed: they function not as neutral repositories but as productive biases.

The Role of the Custom Search Engine

Coupled with the library is a custom search engine that operates on contextual proximity rather than keyword matching alone. It is connected via API to Wolfram Mathematica or to coding environments, enabling specific content to be automatically injected into LLM prompts. The search engine functions as a mechanism for producing friction against generic response patterns (Schulhoff et al., 2024). It introduces disciplinary pressure by surfacing specific, positioned material that the LLM must negotiate rather than bypass. This

approach resonates with recent work exploring how structured knowledge navigation can guide machine learning processes away from generic outputs toward domain-specific design exploration (Pestriakova, Schubert and Petzold, 2025).

The Hybrid Workflow

The method does not operate as a linear pipeline but as a plug-and-play constellation of actors. The workflow comprises: a curated corpus, a custom search engine, retrieved fragments, an LLM, and a human composer. Each actor contributes a distinct capacity, but the constellation is not fixed. Actors can be added, removed, rearranged, or substituted; the design of the constellation is itself a design act. In this model, the LLM is neither autonomous author nor passive tool. It is a connective engine whose outputs are conditioned, redirected, and enriched by the library, and then selected, edited,

THE CONSTELLATION

1001 in 1 – actors and exchanges

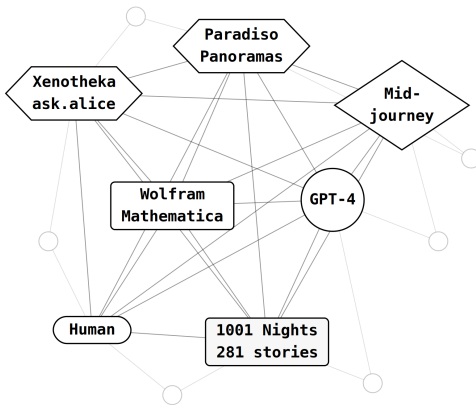


Figure 2
The hybrid workflow. A curated corpus, custom search engine, retrieved fragments, LLM, and human composer form a plug-and-play constellation of actors.

and composed by the human. Writing becomes an act of orchestration rather than generation (Figure 2).

Taken together, these components define a reproducible method. The approach consists of: (1)

Figure 3
View across the
space of '1001 IN 1'.
The scenography
uses LED screens to
create immersive,
shifting
environments
driven by
LLM-generated
compositions.

curating a domain-specific corpus; (2) structuring access through a custom search system; (3) retrieving fragments based on contextual proximity; (4) injecting retrieved material into LLM prompts; and (5) orchestrating iterative transformations across media. These steps can be understood as a five-stage pipeline applicable across different design contexts. The method is intentionally modular, allowing individual components—such as data sources, embedding models, or retrieval strategies—to be replaced without altering the overall workflow. The following sections demonstrate how this method operates in practice.

DEMONSTRATION OF THE METHOD: '1001 IN 1'

The following case demonstrates the application of the proposed method. It is not presented as validation in a quantitative sense, but as an operational instance showing how domain-specific libraries condition and structure generative processes across media.

Why '1001 IN 1' Is Relevant

'1001 IN 1' is a scenographic project that integrates large language models into a logistic framework for recontextualizing the One Thousand and One Nights through contemporary cultural references (Nickl, Bokhari and Roman, 2024). It demonstrates, at scale, how curated datasets redirect LLM behaviour, how prompt cascades generate coherent outputs across media, and how writing becomes the generator of spatial, visual, and atmospheric composition (Figure 3). The project uses 281 stories from the One Thousand and One Nights as narrative substrate, curated authors from Xenotheka, directors from Paradiso, from which are derived curated lists of artists, songs, music genres, and coded prompt structures, all orchestrated through GPT-4 Turbo accessed via the OpenAI API through Wolfram Mathematica, with Midjourney V5 for image generation.



Structure of the Cascade

At the core of '1001 IN 1' is a structured cascade of chained LLM calls in which each output conditions the next, extending the logic of chain-of-thought prompting (Wei et al., 2022) into a multi-step generative pipeline. The system operates as a chain of dependent transformations where a narrative seed is progressively transformed into a coherent scenographic environment. This cascade is driven by continuous interaction with curated domain-specific libraries: Xenotheka introduces stylistic and theoretical positioning through curated authors, while Paradiso injects cinematic logic through films, characters, and directors. Together, they constrain and redirect the generative process away from generic outputs toward situated, culturally dense compositions. The entire process is synchronized through a Wolfram Mathematica script and a database file that contains all generated fields and functions as an operative database, allowing each step to be stored, reloaded, aligned, and reused across the full set of stories (Table 1).

Across this sequence, each step is conditioned by domain-specific inputs, while the cascade relies on the connective capacity of ChatGPT to relate these elements across domains. The Mathematica script binds these elements into one operative chain, while the database preserves the outputs as a synchronized matrix of relations.

Step	Operation	System	Domain-Specific Lens	Output
1	Film Character	ChatGPT	Paradiso (film)	Main protagonist
2	Rewritten Synthesis	ChatGPT	Xenotheka (author) + Paradiso (character)	Story in authorial style
3	Title	ChatGPT	Xenotheka (author)	Story title
4	Triplets	ChatGPT	Xenotheka (author)	Abstract constructs
5	Place	ChatGPT	based on Step 2	Indoor setting
6	Window View	ChatGPT	Paradiso (character + film) + Step 2	Spatial description
7	Window Formula	ChatGPT	Paradiso (director) + Step 6	MJ prompt
8	Table Setting	ChatGPT	1001 Nights (theme) + Steps 2, 5, 6	Table description
9	Table Formula	ChatGPT	Paradiso (director) + Artist list + Step 8	MJ prompt
10	Song (Genre)	ChatGPT	Genre list + based on Steps 2, 5	Track
11	Song	ChatGPT	based on Steps 2, 5, 10	Track
12	Fetish Object	ChatGPT	Paradiso (character) + based on Step 2	Object description
13	Flower	ChatGPT	Paradiso (character) + based on Step 2	Flower description
14	Atmosphere	ChatGPT	based on Steps 2, 5, 6	Adjective list
—	MJ Prompt Assembly	—	based on step 6, 7, 12, 13	4 formatted prompts
15	Image Execution	Midjourney	All assembled prompts	4 images

Table 1
Cascade structure of '1001 IN 1'. The sequential chain of fifteen operations constituting the generative cascade. Each row specifies the operation performed, the system invoked, and the domain-specific lens applied.

Outputs and Cross-Modal Coherence

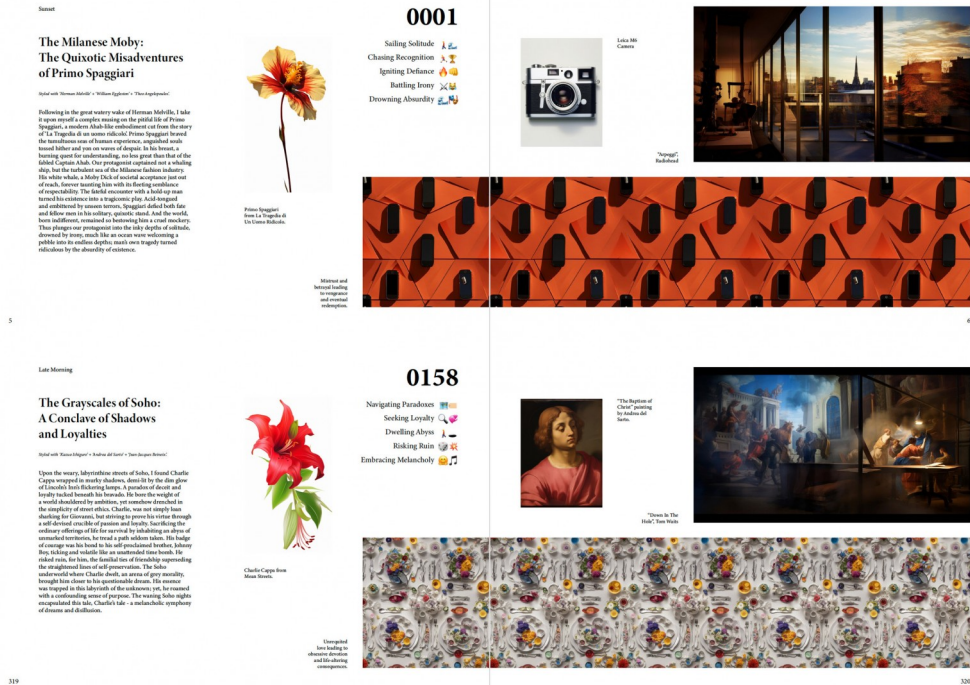
Each of the 281 stories generated a structured JSON record comprising more than 25 interrelated fields: rewritten narrative, title, semantic triplets, place, time, window view, table setting, fetish object, flower, atmosphere, five Midjourney image prompts, song selection, and performance directions. It can be found here: https://alice-ch3n81.net/files/data/1001in1/1001_mechanics.xlsx These outputs are components of a sequential cascade in which each step conditions the next. The cascading structure produces cross-modal coherence: the narrative informs the scenography, the scenography informs the image prompts, and the image prompts reinforce the atmospheric register of the text. Crucially, this coherence emerges from the interplay between probabilistic generation and domain-specific constraints. The outputs were materialized in multiple formats: a physical installation composed of eight large LED screens forming a table and a window, a printed volume compiling all rewritten stories (Figure 4), and a synchronized scenographic

sequence. The system extends beyond textual production into spatial and experiential design.

PEDAGOGICAL APPLICATION OF THE METHOD

The method was further applied in an educational context to test its transferability from synthetic writing and scenographic production to architectural design and built form. The same conceptual strategy—integrating domain-specific datasets, curated search engines, large language models, and computational environments—was extended into architectural education through a design studio at the University of Innsbruck. Students were tasked with developing and constructing two meditation pavilions for Buddhist practice, aligning with Schön's (1983) understanding of design as a reflective practice in which knowing and doing are inseparable. Within the studio, religion was approached not as doctrine but as a dense symbolic and cultural domain: a structured field of rituals, deities, materials, texts, atmospheres, and

Figure 4
Example of a
generated spread
for the book. Each
story is rewritten
through curated
author styles from
Xenotheka,
visualized through
Midjourney
prompts
conditioned by
Paradiso directors.
The full volume is
available online
(studio0more,
2025).



narratives. It functioned as a curated knowledge environment—a library from which students could draw names, stories, material logics, and affective registers. These collections operated similarly to Xenotheka and Paradiso in '1001 IN 1', acting as lenses that guided interpretation, selection, and design decisions. Students began by working with curated corpora of texts, images, and videos, assembling conceptual worlds that framed their projects. Using AI-supported tools alongside conventional architectural methods, they developed proposals through a sequence of transformations: from research to narrative construction, from naming and identity formation to spatial articulation and construction logic. Writing was central—not as description, but as an operative medium.

Students authored texts situating their pavilions within specific religious, geographical, and ritual contexts; produced videos translating these worlds into temporal sequences; and developed both virtual and physical models. The process extended beyond design in a narrow sense. Each pavilion was treated as a character with a name, narrative, and representational identity. AI tools were embedded throughout: LLM-based tools supported textual development; curated cinematic databases and image generators informed visual and atmospheric exploration; additional tools contributed to sound and media production. The result was a fully integrated workflow in which writing, image-making, modelling, and communication formed a continuous system. From



Figure 5
Two built
rammed-earth
pavilions for
Buddhist
meditation.

an initial set of 22 proposals, two projects were selected and realized as full-scale rammed-earth pavilions (Figure 5). The studio process and student work are documented in the student book *On Religion* (studio0more, 2025). The pedagogical implications are significant. Students did not simply use AI as a tool; they learned to construct coherent worlds, articulate positions, and translate narrative and symbolic density into material form. The process encompassed not only design, but also communication, funding, negotiation, and execution—linking conceptual development to real-world constraints and collaborations. Across both cases, consistent operational patterns were observed: (1) outputs exhibited increased terminological specificity aligned with the curated corpus, (2) narrative structures reflected the internal logic of the selected libraries, and (3) iterative prompting led to progressively more coherent and domain-consistent results. These observations indicate that the method effectively constrains and directs generative outputs without requiring fine-tuning of the underlying models.

DISCUSSION AND IMPLICATIONS

Main Claim Restated

The aim of this work is not to optimize model performance but to structure meaningful interaction between domain-specific knowledge and generative systems. The evidence from both demonstrations supports the central thesis: LLMs are powerful but generic by default. Domain-specific libraries provide direction, friction, and lineage. Through this interaction, writing shifts from description toward architectural articulation—encompassing prompting, structuring, and coding. The curated library does not replace the LLM; it conditions its field of articulation, transforming it from a universal connector into a situated, context-sensitive instrument. Unlike general-purpose prompting strategies, which rely on implicit context, the proposed approach externalizes context into structured libraries, making the conditioning of outputs explicit, reproducible, and transferable.

Educational Implications

For architectural education, the implications are substantial. Students learn to construct and navigate

knowledge environments: to curate corpora, design search structures, and stage relationships between texts, images, and ideas. Authorship shifts from manually producing every sentence toward selecting datasets, framing queries, orchestrating relations, and critically editing outcomes. This mode of working is closer to architectural practice than generic chatbot use; architects have always designed through selection, reference, and positioning rather than *ex nihilo* creation. The method further suggests that writing should be understood as an architectural practice in itself—an act of composition, selection, and contextual weaving. Coding, searching, and querying become forms of architectural literacy (Bühlmann et al., 2015). Following Stiegler's (2010) analysis of digital technologies as pharmacological instruments, AI is not a threat to authorship but a medium through which authorship is exercised differently: less as isolated production, more as the orchestration of structured knowledge.

Limitations

Several limitations must be acknowledged. Curated libraries are inherently biased, and their composition strongly shapes outcomes. The method depends critically on the quality of curation; poorly constructed datasets lead to poorly directed results. Evaluation remains partly qualitative: assessing disciplinary specificity cannot be reduced to a single metric, and distinctions between generic and situated outputs often rely on judgment. Moreover, the method is particularly effective for conceptual and compositional work but does not guarantee factual correctness, as outputs remain probabilistic, and its effectiveness depends on the quality and coherence of the curated libraries. The approach requires computational literacy and technical infrastructure that may not be available in all educational contexts. Nevertheless, differences between generic and library-conditioned outputs were consistently observable across both cases in terms of stylistic specificity, referential density, and cross-modal alignment. Future work may

formalize these observations through comparative studies measuring lexical diversity, domain-specific reference frequency, or structured expert evaluation.

Broader Outlook

Looking forward, similar models can be applied across design disciplines where domain-specific knowledge and positioned discourse are essential. Future architectural pedagogy may increasingly rely on custom libraries, search systems, and orchestration workflows rather than general-purpose AI alone. The key question is no longer whether designers will work with AI, but what kinds of libraries, biases, and compositional frameworks will allow that work to remain disciplinarily grounded (Carpo, 2017; Terzidis, 2006).

CONCLUSION

This paper has presented a method for structuring AI-assisted architectural writing through domain-specific libraries. General-purpose LLMs tend to flatten disciplinary specificity; domain-specific libraries act as focus lenses. Through them, AI-assisted writing becomes a situated architectural act: not the production of generic content, but the orchestration of curated knowledge, stylistic reference, and compositional judgment. '1001 IN 1' demonstrates this: a structured prompt cascade conditioned by Xenotheka, Paradiso, and curated cultural datasets generated 281 coherent scenographic environments spanning text, image, sound, and performance — a coherence that follows not from the LLM alone but from the library-mediated workflow. The design studio extends this logic into pedagogy and built work: students who constructed curated conceptual worlds and translated them into design decisions produced projects that were positioned, narratively dense, and materially grounded. In the age of AI, the question is no longer whether architects will write with machines, but how they will construct the contexts within which such writing takes place. Domain-specific

libraries thus emerge not as auxiliary datasets but as infrastructure shaping how architectural knowledge is produced, navigated, and articulated.

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