

DesignerlyLoop: Bridging the Cognitive Gap through Visual Node-Based Reasoning in Human–AI Collaborative Design

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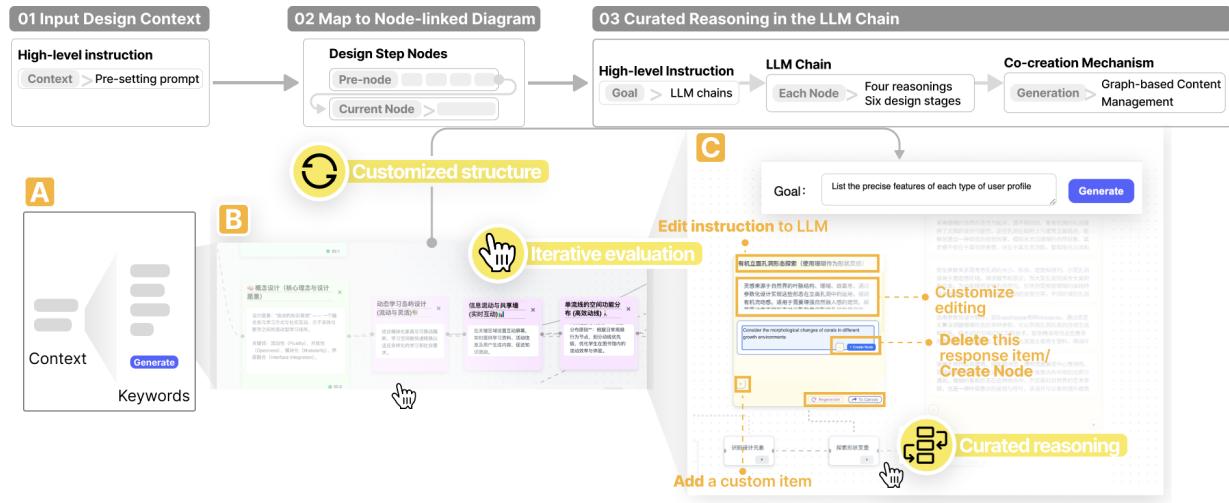


Figure 1: Overview of *DesignerlyLoop*, an LLM-based design tool, highlighting its three key mechanisms. The workflow starts with (1) Input Design Context. Then, (2) Map to Node-linked Diagram enables the Customized Structure mechanism (B). Finally, (3) LLM Chain leverages the Curated Reasoning mechanism to generate solutions (C). An Iterative Loop allows for continuous refinement by switching between the design canvas and reasoning views (B, C).

Abstract

Large language models (LLMs) offer powerful support for design tasks, yet their goal-oriented, single-turn responses often misalign with the nonlinear, exploratory nature of design processes. This mismatch creates a cognitive gap, limiting designers' ability to articulate evolving intentions, critically evaluate outputs, and maintain creative agency. To address

these challenges, we developed *DesignerlyLoop*, a visual node-based system that embeds LLM reasoning chains into the design workflow. The system enables designers to externalize and curate reasoning structures, iteratively organize intentions, and interact with LLMs as dynamic cognitive engines rather than static answer providers. We conducted a within-subject study with 20 designers, combining qualitative and quantitative methods, and found that *DesignerlyLoop* enhanced creative reflection, design quality, and interaction experience by supporting systematic engagement with both human and machine reasoning. These findings highlight the potential of structured, interactive visualization to transform human–AI co-creation into a reflective and iterative design process.

CCS Concepts

- Human-centered computing → Human computer interaction (HCI); Empirical studies in HCI;
- Applied computing → Computer-aided design.

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Keywords

human-AI collaboration, reasoning, design, creativity, AI-assisted design, Large language model (LLM), LLM chain

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1 Introduction

Recent works support the superior capabilities of large language models (LLMs), such as Generative Pre-trained Transformer 4 (GPT-4) [68], in addressing the diverse needs of design process [6, 86]: design ideation [16, 36, 83], concept development [3, 49, 98, 100, 117], assistant materials [7], and problem-solving [26, 95, 105]. As design is a cognitive demanding activity that involves navigating ambiguity while iteratively refining outputs toward an intended goal [10, 48, 54], designer often engage with LLMs through multi-turn dialogues to clarify core ideas or address complex problems. In such scenarios, designers frequently encounter challenges when attempting to explore open-ended design intent. To address this, building a tool to support “exploratory design intent” during a non-linear process is significant. This capability is crucial for fostering open-ended exploration [20, 31], enabling designers to externalize evolving ideas [27, 91], navigate ambiguity [5, 79], and iteratively refine intent [23, 69] through structured yet flexible interaction with LLMs. It empowers designers to maintain creative agency while benefiting from the generative and analytical strengths of the model.

However, a fundamental cognitive gap exists between designers and LLMs. While LLMs typically operate through direct, goal-oriented reasoning to produce definitive answers, design processes are nonlinear, ambiguous, and exploratory, driven by loosely defined intent and iterative sense-making. This mismatch forces designers to navigate the black-box nature of LLMs with little visibility into underlying reasoning [58, 108, 114], making it difficult to evaluate or steer system behavior. Moreover, single-turn interaction patterns constrain the articulation of vague intent, often yielding generic or irrelevant responses [38, 113]. These limitations reduce opportunities for critical thinking and intentional direction-setting [2, 109, 117]. Without scaffolding, designers risk skipping key cognitive steps such as planning, execution, and reflection, leading to over-reliance on LLM outputs and weakened independent judgment [93]. Addressing these gaps requires systems that not only generate outputs but also scaffold exploratory reasoning, reflection, and interpretability throughout the design process.

One promising solution is visualizing structured cognitive representations used by designers (e.g., through mind map diagrams)- to define goals, apply reasoning strategies, and navigate ambiguous problems [44, 76, 80, 81, 93, 96, 104]. Design

field often employs this visualizing method. Current graphic-based LLM tools have focused on mapping iterative ideas or externalizing evolving contexts in a designer-LLM co-creation (e.g., [16, 83, 109]), as well as non-linear organization and interaction (e.g., in design [56, 57] and non-design context (e.g., [47, 116])). By articulating and visualizing their evolving design intent and underlying reasoning structures, designers can create shared representations that contextualize LLM outputs, reduce ambiguity, and support reflective iteration [109]. In this way, this visualized method not only scaffold human thinking but also enable LLMs to participate in the co-creation of design, forming a dynamic and collaborative reasoning process [4, 9, 41].

However, existing studies overlooked intentionally **curated reasoning** in the co-creation design process. Despite explored LLM-driven reasoning strategies in co-creation (e.g. *Ideation-Web* [83] and *CoExploreDS* [16]), designers have limitation on controllability of reasoning during evolving context. For instance, *CoExploreDS* applies various reasoning strategies but still produces single-turn outputs, lacking user controllability supporting for interactive, multi-turn reasoning that aligns with the evolving needs of design. In addition, bridging the cognitive gap requires **iterative evaluation** and **customized structure** (e.g., representing hierarchy, order, relationship) using graphic-based tools. First, this process requires iterative loops to support reflective evaluation of both human- and machine-generated reasoning [93]. Second, this process need to support designers to organize intent using hierarchical, temporal, or relational logic, rather than fixed-structure graphs in most existing tools. Supporting diverse organizational formats is essential for externalizing varied cognitive process.

Inspired current tools curating LLM chains that benefit user controllability using explicitly exposing reasoning logic and connection structure that allows to continuous iteration (e.g., [46, 93, 107, 108]), we highlights the significance of supporting design intent is that tools must support “articulating reasoning structures” and “mapping system behaviors” [93]. Using graphic visualizing method, this involves (1) curating system reasoning models (2) modelling user intent, and (3) supporting user-driven iteration. Thus, our research questions are: *How can a graphic co-creative system be designed to support reasoning process of LLM during exploring design intent, bridging the cognitive gap between designer and LLMs?*

To address these challenges, we propose *DesignerlyLoop*, a visual node-based system that integrates a curated LLM reasoning chain into designer-LLM co-creation. *DesignerlyLoop* combines a diagrammatic interface with real-time LLM execution, enabling designers to construct, test, and iterate on multi-step reasoning. By embedding LLMs directly in the design environment, the system offers immediate semantic feedback, supports prompt chaining, and externalizes users’ evolving design logic. In a within-subject study with 20 designers, *DesignerlyLoop* supported both the formation of design intent and critical reflection. Qualitative and quantitative results indicated improvements in interaction experience, creativity, and

design quality, as participants systematically engaged with reasoning and actively curated LLM outputs rather than passively accepting suggestions. These findings suggest that embedding LLMs as structured, interactive reasoning engines can foster more reflective, iterative, and higher-quality human-AI co-creation.

Our contributions are threefold: (1) Proposing key insights of graphic-based designer-AI collaborative tools for forming design intent, including three challenges and design guidelines in a formative study; (2) Developing *DesignerlyLoop* processing a two-tier structure reasoning process with customized organization and iterative evaluation by combining the design process and AI thinking path; (3) Demonstrating the benefits of *DesignerlyLoop* in supporting design intent with better experience and higher creativity supports during human-AI collaboration process.

2 Related Works

2.1 Forming Design Intent

2.1.1 Defining Design Intent. Design intent rarely emerges fully formed. Instead, it unfolds iteratively through sense-making, prototyping, and reflection as designers engage with evolving constraints and materials [35]. In such exploratory process, intent may manifest as ambiguous metaphors or affective narratives in the early phase, later refined into clearer propositions [90]. HCI tools—such as sketch canvases, versioned annotations, and timeline overlays—can scaffold this gradual externalization and stabilization of intent over time [16, 22, 59, 82, 83, 94].

2.1.2 Forming Intent from Diverse Supports. Creative design processes oriented around the articulation and refinement of intent require nuanced system support that accommodates the evolving and situated nature of intent formation. Drawing from cognitive models of creativity and interaction design literature [30, 45, 65, 74, 81, 84, 103], we identify three critical dimensions along which design tools must support intent-driven practices:

Non-Linear design loops. Creative design intent does not progress linearly but evolves through recursive loops involving exploration, reinterpretation, and reformulation [13, 24, 29, 117]. Designers fluidly transition between divergent/convergent thinking across research, ideation, and critique phases [10, 57]. This loop feature necessitates tools that accommodate: (1) Intent reformulation triggered by new constraints, user feedback, or serendipitous discoveries; (2) Stage-agnostic input mechanisms that allow ideation at any point in the process [32, 40]; (3) Concept tracing features and timeline visualization to revisit and branch design paths [93]. Systems should thus enable temporal fluidity, branching, and re-entry, rather than enforce prescriptive workflows.

Diverse representational forms. Design intent manifest heterogeneously across practitioners even when addressing identical goals. Diverse solutions emerge through varied emphasis on visual semantics, functional aims, user considerations,

or prototype fidelity, reflecting distinct value judgments and objectives [15, 52]. This diversity necessitates interfaces that fluidly adapt to individual designer's evolving representational needs.

Dialogic co-creation. Building on Schön's notion of “conversation with materials”, design is an iterative dialogue where emerging artifacts influence cognition and action. Intent formation is not solely internal but shaped through back-and-forth interaction with evolving prototypes, sketches, and other intermediaries [74]. Design tools should therefore treat artifacts not just as outputs but as conversational partners—surfacing meaningful responses that invite reflection, reinterpretation, and thematic development.

2.1.3 LLM Capabilities for Building Design Around Intent. The breakthrough of prompting LLMs (e.g. GPT-4o [68], Deepseek, Claude) exhibit three core capabilities enabling novel approaches to intent-driven design: First, LLMs' advanced natural language comprehension allows designers to verbally externalize and refine ambiguous intent through iterative dialogue [68]. This capability transforms linguistic expressions directly into executable specifications, facilitating on-demand tool creation without technical retraining. The recursive interaction pattern supports continuous intent disambiguation via semantic negotiation [14].

Second, as reflective collaborators, LLMs demonstrate cognitive partnership across creative domains [12, 71, 112]. They enable *bidirectional* sense-making where both human and AI agents progressively adapt their reasoning, surpassing tools requiring unilateral user adaptation [30, 85].

Third, LLMs perform abductive inference—generating plausible hypotheses under uncertainty—through frameworks like ReAct that integrate reasoning with action [111]. This capability facilitates contextual intent inference with under-specified goals, consequence anticipation prior to implementation, and comparative solution evaluation. Crucially, LLMs enable analogical adaptation of known forms to novel problems through cross-domain knowledge transfer. This aligns with Peirce's conception of abduction as “inference to the best explanation” [1]. By translating abstract concepts into executable specifications while maintaining semantic coherence across iterative refinements, LLMs scaffold design intent as a dynamic cognitive process co-negotiated between human and artificial agents.

2.2 AI Graph-Based Creativity Tool and Human-AI Co-Creation

The fundamental cognitive gap between LLM and designer makes it difficult for designers to align their evolving design process with the structured outputs provided by LLMs. LLM often response with direct, objective-driven, and turn-based outputs (e.g., via instructive prompts like “You are a [role]”) [2, 93, 109, 117]. In contrast, design is inherently non-linear, iterative, and ambiguous, often characterized as dealing with “ill-defined problems” due to incomplete or evolving problem information [88].

Graph-based interfaces resolve this gap by enhancing editability and information representation, thereby supporting nonlinear design workflows. Such interfaces enable refinement, regeneration, and navigation across design iterations [16, 19, 47, 56, 57, 75, 83, 87, 107, 109]. These tools extend established visual methods (e.g., mind maps, concept maps, node-link diagrams) that scaffold ideation and systems thinking in design research [11, 67]. By facilitating multi-turn iteration and pipeline composition, they introduce novel LLM interaction paradigms. Shokrizadeh et al. [87] enables UI ideation through version navigation on a canvas. Lin and Martelaro [57]'s *Jigsaw* system supports cross-modal AI pipeline construction (e.g., integrating ChatGPT and Midjourney). He et al. [36] employs an LLM-enhanced canvas for group ideation with structured sticky notes. Graph structures further serve as intermediary representations for prompt steering by decomposing text prompts into hierarchical elements [74, 110]. Systems like *AI-Instruments* [74] utilize fragmented prompt cards to enable continuous intent refinement. However, some inherent limitations of current graph-based approaches constrain their design support capability. Limited controllability and interpretability can erode human trust in AI systems [55, 72, 97]. Moreover, users may become overwhelmed by the accumulation of prompts and AI-generated outputs during extended exploration [33].

Designer-LLM co-creation shows particular promise during conceptualization. AI agents function as co-creators that introduce varied inputs in parallel, enhancing conceptual diversity [39, 62, 63]. Empirical evidence indicates that even brief exposure to AI-generated ideas stimulates novel conceptual directions [53]. However, persistent concerns regarding authorship ambiguity, over-reliance, and diminished human agency require resolution [73]. Scholars have increasingly employed visualized approaches to represent co-creation process, not only increasing model understanding but also preserving user ownership and intentionality [2, 74, 83, 94, 109]. *Ideation Web* [83], for instance, empirically applied four distinct human-AI co-creation strategies in design ideas, yet its single-turn generation mechanism still limited user controllability. One type of these studies focusing on reasoning processes in such co-creation processes have shown potential to address this issue. *Jamplate* [109] employs design templates (i.e., Five Whys, Competitive Analysis) to facilitate progressive, step-wise solution refinement and cognitive elicitation. However, its use of fixed node-link structures inadequately captures the evolving nature of design processes, thereby constraining emergent exploration. *CoExploreDS* [16] fills this gap by employing node-linked diagram enables track and visualize idea development, capturing logical relationships and conceptual similarities. Furthermore, this work leverage analogical, inductive, abductive and analogical reasoning to guide LLM thinking during ideation [16].

Nevertheless, these systems still provide insufficient user control over the underlying reasoning processes. Users are left with multiple rounds of what is essentially one-time generated content to continually refine. Externalizing reasoning paths

enables designers to evaluate LLM cognition and better align outputs with design goals. Our work aims to explore a more explicit externalization of reasoning strategies to extend this boundary by enabling bidirectional integration between design representations and LLM reasoning—transforming visual design diagrams into editable interfaces for AI interaction.

3 Formative Study

Study Goal. The formative study aimed to explore how designers construct and externalize their design intentions with the support of LLMs. We focused on identifying current practices, challenges, and expectations for LLM-assisted design tools, in order to inform the design of our prototype system.

Participants. We recruited eight designers (5 female, 3 males) aged 23–30 year. Among them, four were experienced experts (e.g., visual communication designer, UX designer, urban designs) with over eight years of professional practice. Given the prevalence of ChatGPT as a widely adopted LLM, our study centered on participants' experiences with ChatGPT or similar tools.

Procedure. The study consisted of two parts. First, we conducted a 30-minute hands-on task with three participants, asking them to create a design concept using GPT and present their outcomes in *Figma*, a popular visual design tool. We recorded the prompts they used and thematically coded the resulting use cases. After this task, participants engaged in a short semi-structured interview reflecting on their workflow and tool experience. Second, we conducted in-depth semi-structured interviews with the remaining participants. These interviews focused on three core areas: (1) how designers typically form design intent, (2) what kinds of information they provide to GPT during this process, and (3) how they envision future AI-based tools to better support conceptual development.

Data Collection and Analysis. All interviews were conducted in Chinese via video calls and lasted 45–90 minutes. Audio recordings were transcribed using iFlytek and manually corrected for accuracy. Chinese excerpts used in analysis or reporting were translated into English with DeepL; translations were subsequently reviewed and revised to maintain conceptual fidelity and preserve design-specific terminology.

We employed reflexive thematic analysis [8]. Two researchers independently performed open coding on the full Chinese transcripts and field notes from the 30-minute hands-on sessions. Code sets were compared in weekly calibration meetings, during which discrepancies were resolved and the codebook was iteratively refined. A senior researcher audited the evolving codebook and thematic structure to ensure coherence and methodological rigor. After finalizing the codebook, both coders applied it across the dataset using an inductive–deductive strategy aligned with the research questions. Analytic memos were maintained throughout to document coding decisions

and translation clarifications. Themes were derived by synthesizing recurring patterns and triangulating insights from interviews and observed design practices.

3.1 Forming Design Intent and AI Support Needs

Designers typically initiate the formation of design intent through a non-linear, internally guided process grounded in personal philosophies, contextual awareness, and domain knowledge. Rather than using GPT to define initial goals, participants emphasized leveraging their own frameworks and relying on the model to support specific sub-tasks. For example, P4 remarked that “*designers already have their own logic and frameworks in mind*,” using GPT primarily for assistance with underexplored areas such as demographic scenarios or spatial constraints.

Participants described interacting with GPT as if it were an all-knowing interlocutor, integrating it across all stages of the design process. As P2 noted, “*I use GPT whenever I’m stuck or need a new perspective—it’s like chatting with someone who knows everything*.” Designers often input large amounts of fragmented thoughts—“*bits and pieces*”—which GPT helps to structure into coherent concept maps. It also excels at summarizing, expanding, and organizing these fragmented inputs, thereby enabling clarity during early ideation. P6 described a practice of creating project-specific folders, each containing multiple conversations, noting that “*the more we talk, the more it understands the project*.” In addition, GPT was valued for accelerating research tasks such as user journey mapping, persona creation, and gathering background information. It was also used to simulate stakeholder perspectives, aiding empathy-driven design.

3.2 Challenges of Using AI to Construct Design Intent

3.2.1 C1: Shallow Reasoning and Fragile Conceptual Development. Participants frequently used GPT to articulate and shape design ideas, but consistently faced shallow reasoning and fragile conceptual outputs. Responses were often generic, repetitive, and risk-averse, limiting meaningful synthesis. As P1 noted, “*It talks a lot, but nothing really useful*;” P5 added that GPT “*rarely makes explicit how those patterns are reasoned*”. Experienced users mitigated issues via curated examples or structured templates (P3), but novices struggled without extensive prompt engineering. GPT was mainly employed for narrow tasks such as generating point-of-view statements or blueprints (P4, P8), acting as a modular assistant rather than a co-creator (P7).

3.2.2 C2: Contextual Forgetfulness and Information Fragmentation. Participants reported breakdowns in contextual continuity after 5–10 conversational turns, with GPT losing track of earlier references or reusing terms inconsistently. P4 remarked, “*Sometimes it brings in examples from another project I mentioned days ago*”. This necessitated repeated restatements

of goals, increasing cognitive load. Experts occasionally used “*design folders*” to preserve topic fidelity, but novices were more prone to drifting focus. Designers highlighted that multiple factors (e.g., safety regulations, lighting) intersect, requiring GPT to link and contextualize concepts across turns, a capability currently limited.

3.2.3 C3: Limited Support for Core Design Intent and Multi-Dimensional Integration. GPT struggled to engage with core design intent and conceptual frameworks, producing outputs often generic and lacking nuanced rationale. P7 observed, “*GPT’s outputs tend to miss the subtle reasoning required to align with established design ideologies*”. Participants used GPT mainly for pattern recognition after intent formation (P5, P2), and envisioned future systems allowing intervention checkpoints and modular assistance to integrate fragmented knowledge (P8).

3.3 Design Goals

3.3.1 DG1: Node-Based Scaffolding for Structured Design Reasoning. To address shallow reasoning (C1), LLM tools should support decomposition of abstract ideas into modular reasoning tasks, enabling stepwise exploration of metaphors, aesthetics, and design logic [38, 113]. Nodes host focused prompt templates targeting specific cognitive functions (P1, P6), enhancing conceptual depth. P2 noted, “*It helps me push my ideas deeper when the model knows exactly what kind of decision I’m trying to make*”.

3.3.2 DG2: Cross-Node Context Persistence for Sustained Conceptual Coherence. To mitigate contextual forgetfulness (C2), systems should embed memory slots or topic anchors within nodes, tracking evolving goals. P7 commented, “*If it could just remember what I told it three nodes ago, I wouldn’t have to reset everything all the time*”. Linking related nodes enables LLMs to synthesize insights across threads, supporting layered, long-range ideation (P4).

3.3.3 DG3: Configurable LLM Chains for Multi-Dimensional Design Integration. For holistic synthesis (C3), systems should allow users to configure LLM chains integrating diverse concerns such as environmental, demographic, regulatory, and aesthetic factors. P3 highlighted, “*It’s not about listing ideas—it’s about threading them into something meaningful*”. Chains orchestrate multi-node reasoning and provide checkpoints for intermediate synthesis (P8, P4).

3.4 Prototyping Design and Iteration

3.4.1 Initial Prototype Design. To translate the design goals (DG1–DG3) into a tangible system, we first developed a minimum viable prototype (MVP) that captured the essential mechanisms of our approach. The MVP was organized around three core panels: Based on DG1–DG3, the prototype supports curated reasoning at both design and LLM levels, with three panels: 1) design pipeline grounding (*Design Context Builder*);

2) design canvas (*Design Reasoning Canvas*); 3) LLM chain (*LLM Reasoning Chain Viewer*).

3.4.2 Prototype Iteration. We then conducted two co-design workshops with six HCI and UX experts to iteratively refine the prototype. Each workshop began with a demonstration of the prototype, then walkthrough of the MVP and a guided design task, followed by critical reflection and structured feedback. This process enabled us to assess the usability of core features, identify breakdowns in workflow alignment, and prioritize enhancements that would increase reflective engagement without overloading users.

3.4.3 Iteration Outcomes. Insights from the workshops informed a set of key refinements to the prototype: (1) exporting AI chain node outputs to the main design canvas; (2) automatic chain generation from design-level prompts; (3) LLM-driven determination of reasoning type per node; (4) unique LLM chain usage per node; (5) grouping/classifying nodes; (6) user-customizable editing and organization of LLM outputs. Collectively, these refinements advanced the prototype from a proof-of-concept to a more robust system aligned with expert design practices.

4 System Design

To support designers in co-creating with LLMs and forming design intent, we developed ***DesignerlyLoop***—a visual node-link diagram system that scaffolds controllable LLM reasoning for goal-aligned human–AI collaboration. The system forms a continuous iterative loop that enables users to articulate high-level design goals, externalize their cognitive process, and iteratively engage with LLM-generated reasoning chains. *DesignerlyLoop*'s integrating capabilities help users: (1) understand and evaluate the *LLM's cognitive process*; (2) re-align LLM behavior with user intent.

4.1 *DesignerlyLoop* Interaction Design

As illustrated in Figure 2, *DesignerlyLoop* comprises three primary panels: Panel A *Design Context Builder*, Panel B *Design Reasoning Canvas*, and Panel C *LLM Reasoning Chain Viewer*. Design intent is treated not as a fixed goal but as a moving target shaped through iterative loops.

4.1.1 Panel A: Design Context Builder. Panel A supports alignment between high-level design intent and concrete execution-level steps (DG3). Users define design background, goals, and stylistic preferences (Figure 2-A). Based on this input, the system automatically generates a sequenced *design nodes*—a structured list of design process (Figure 2 a.2) forming the foundation for downstream processes. Users can edit keywords to tailor the node-link diagram in Panel B (Section 4.1.2).

4.1.2 Panel B: Design Reasoning Canvas. Panel B externalizes and structures evolving design steps via a customizable, node-based digital canvas (Figure 2-B). Each node contains editable content, including a title and segmented blocks documenting

subgoals, hypotheses, or cognitive tasks (e.g. “Concept Design,” “Dynamic Learning Island Design” in Figure 2-B). Users can flexibly add, remove, reorder, or connect *design nodes*, as well as using a node with content generated by AI, *AI node*, to override or supplement existing diagram structures. Node colors, layouts, and link can be customized to indicate cognitive paths or design phases. Multi-path linking and reordering enable parallel exploration of alternative directions. Panel B scaffolds alignment between the user's design cognition (DG2) and the LLM's structured understanding.

4.1.3 Panel C: LLM Reasoning Chain Viewer. Panel C enables the generation of an *LLM reasoning chain* (Figure 2 c.2) embedded within a *design node* within Panel B. By double-clicking a *design node*, users open Panel C and specify a “goal” in natural language, which guides LLM reasoning style and exploratory scope (Figure 3). The panel then produces a multi-step chain with sequential or divergent (parallel) structures, making the LLM's reasoning process explicit. Each chain node is aligned with both a design stage of the Double Diamond model [77] and one of four reasoning methods—inductive, deductive, abductive, or analogical [16] (Figure 4; detailed prompts in Appendix A.3.1). Figure 5 illustrates two representative chain forms, showing how reasoning methods are applied at the node level.

For co-creation, users can add, delete, revise, annotate, and reorder nodes (Figure 2 c.4). *LLM Reasoning Chain Viewer* further supports human–AI collaboration through functions such as: *Addition*—introducing new ideas or contextual details, which the LLM integrates into supplementary nodes; *Deletion*—removing irrelevant nodes, prompting the LLM to adapt reasoning paths; *Revision*—adjusting wording or scope, leading the LLM to regenerate content; and *Prompt refinement*—reformulating inputs to explore alternative trajectories. Users can also regenerate content by editing the node title and clicking “Regenerate” (Figure 2 c.5).

Once refined, nodes can be externalized as sticky notes in Panel B or C via “Create Node”, integrated into the evolving diagram through “Output to Canvas” (c.6), or saved for later iteration (c.7). This reciprocal workflow enables designers to steer ideation through targeted interventions, while the LLM expands and operationalizes their intent into structured reasoning artifacts.

Panel C addresses **DG1: Enabling curated construction and adjustment of LLM reasoning chains** by supporting controllability, co-creation, and subgoal iteration. By mapping LLM outputs to interpretable reasoning categories, the system enhances transparency and empowers users to direct problem-solving. Bidirectional linkage between reasoning structures and design representations enables fluid co-creation where visual structure actively embody reasoning logic, deepening human–AI alignment.

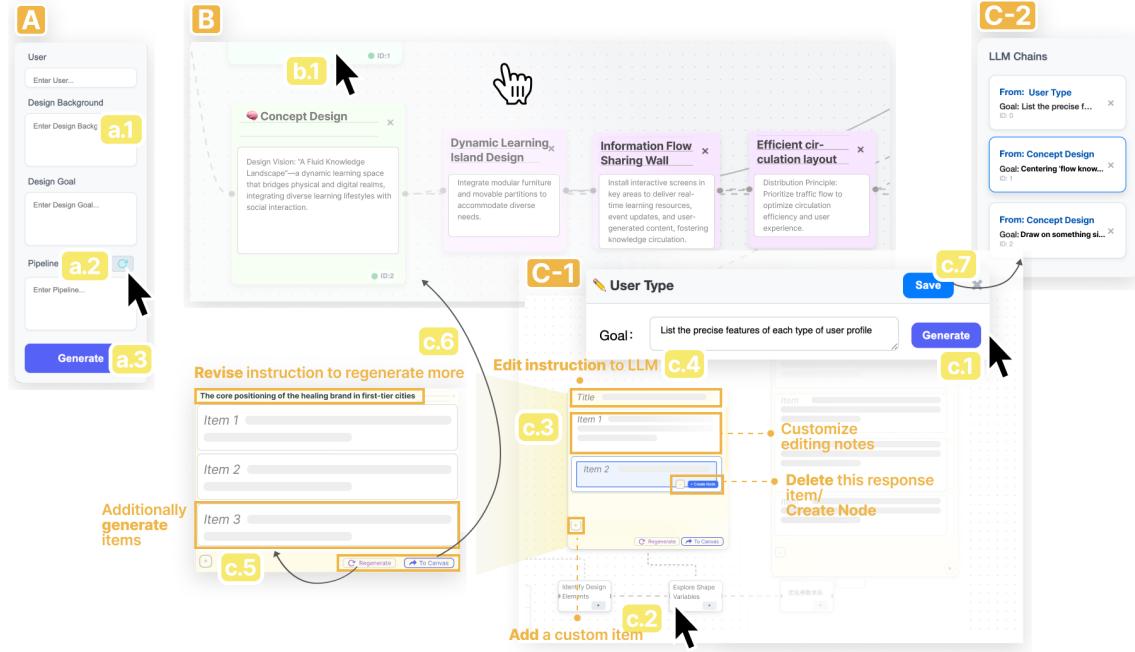


Figure 2: DesignerlyLoop comprises three main interfaces: (A) *Design Context Builder Panel*, (B) *Design Reasoning Canvas*, and (C) *LLM Reasoning Chain Viewer*. Users input design context in (a.1), generating an editable keyword pipeline (a.2). Clicking “Generate” (a.3) produces a node-link diagram in (B), supporting customized edits (e.g., add, delete, modify nodes). Double-clicking a node (b.1) opens (C-1), where users specify goals (c.1) and obtain LLM-generated reasoning nodes (c.2). Each node offers multiple design suggestions (c.3) and co-creation functions (c.4), including content addition, deletion, revision, or regeneration via prompt refinement (c.5). Finalized outputs can be “Output to Canvas” (c.6), saved (c.7) and checked alongside the canvas (C-2).

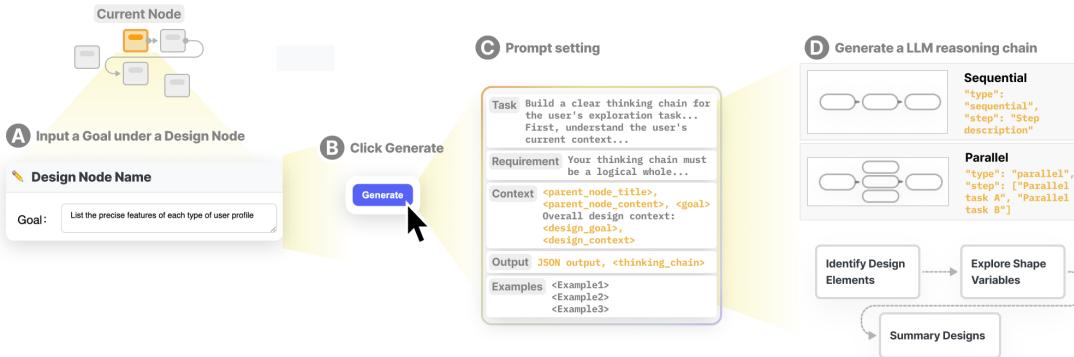


Figure 3: Pipeline for LLM chain generation by the designer in Panel C. When double-clicking a design node, Panel C opens as a popup, where users (A) input a specific “goal” for in-depth exploration under the current *design node*; (B) click “Generate” to (C) map the input into structured prompts, including task, requirements, context, output, and examples; and (D) produce an *LLM chain* that generates both sequential and parallel chain structures with prompt requirements and output formats.

4.2 DesignerlyLoop for Human–LLM Collaboration

These three panels collectively form an integrated reasoning loop that supports designers in iterating between goal articulation, design structuring, and LLM collaboration. Specifically,

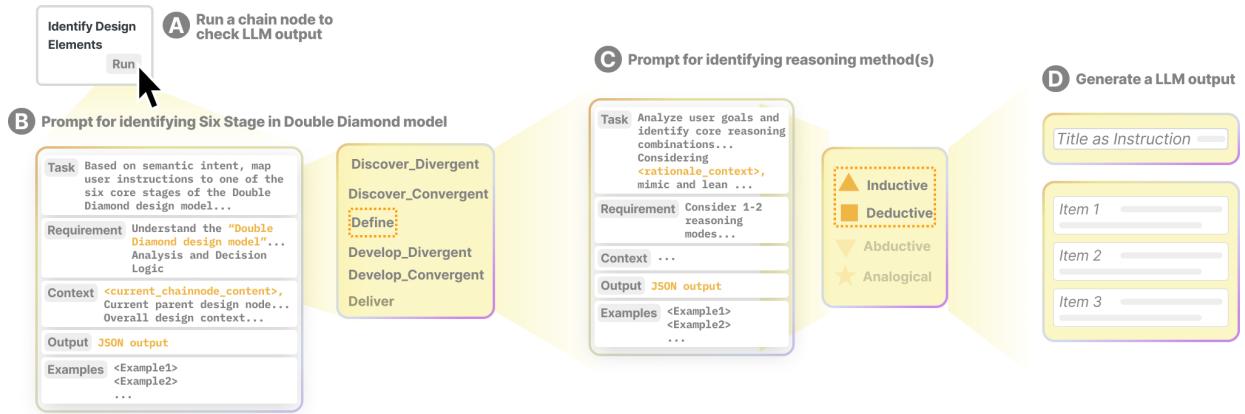


Figure 4: Pipeline for LLM output generation within each chain node in *Panel C*, where users (A) “Run” a chain node to obtain the initial LLM output. The system then (B) applies an LLM prompt to identify the corresponding design stage in the Double Diamond model (Appendix A.3.2) and (C) applies another prompt to specify the reasoning method(s) (Appendix A.3.1). Finally, (D) the system generates the refined LLM output accordingly.



Figure 5: Generated reasoning chains in *LLM Reasoning Chain Viewer* may be sequential or parallel. Each chain node combines a primary and secondary reasoning method, selected from inductive, deductive, abductive, or analogical reasoning.

Panel A *Design Context Builder* captures abstract design goals and preferences, Panel B *Design Reasoning Canvas* externalizes and elaborates the user’s cognitive process via node-based mapping, and Panel C *LLM Reasoning Chain Viewer* visualizes and supports revision of the LLM reasoning chain in response to user feedback. This loop enables designers to reflectively engage with the LLM, enhancing transparency, creative control, and alignment between intent and generation throughout the co-design process.

4.2.1 Example User Walkthrough. To illustrate *DesignerlyLoop* in action, we present a walkthrough scenario based on an interface design. Designer Lin explores layout strategies for an interactive storytelling app for children.

The session begins in Panel A *Design Context Builder*, where Lin defines a high-level design brief: “Create a playful and accessible storytelling interface for children aged 5–8.” They specify preferred goals and constraints in the “*Design Goal*” field (e.g., “low reading level,” “visual-first interaction”) and tag the style as “whimsical and exploratory.” The system uses this input to generate a sequenced design pipeline, such as: (1) *story background*, (2) *onboarding interaction*, (3) *layout structure*, (4) *navigation flow*, (5) *personalization options*.

Next, the user moves to Panel B *Design Reasoning Canvas*, where the pipeline is visualized as editable *design nodes*. Lin

inspects and refines the structure, adding a node for “multi-sensory interaction” that was absent in the generated pipeline. Each node can be annotated and expanded with subthreads of exploration, creating a cognitive map of the evolving design process.

When deeper reasoning is required—e.g., structuring “on-boarding for non-readers”—Lin double-clicks the relevant node, triggering Panel C *LLM Reasoning Chain Viewer*. The system generates a multi-step LLM reasoning chain, with suggestions such as “use audio prompts,” “add avatar-based guidance,” and “progressive disclosure of functionality.” Lin evaluates, re-orders, and revises steps, updating the underlying reasoning graph.

Throughout the session, Lin iteratively switches between panels, refining goals (Panel A), restructuring the conceptual map (Panel B), and interrogating or editing LLM outputs (Panel C). This dynamic interplay fosters not only idea generation but also reflection, traceability, and cognitive alignment across the design process.

4.3 System Implementation

We implement the *DesignerlyLoop* as node-based application, technical framework is illustrated in Figure 6. The critical information regarding design process and its associated LLM reasoning chains are stored as node-based graph data structure in the frontend. This approach provides a powerful model that both frontend and backend can take advantage of. For frontend, the graph serves as an intuitive visual representation that directly supports non-linear design evolution and supports complex design trajectories, giving users the freedom to explore multiple creative directions simultaneously without losing design context. And while the frontend provides an intuitive interface, the true power of *DesignerlyLoop* lies in the backend’s ability to process the graph-based design data. Specifically, backend is implemented to go beyond simple

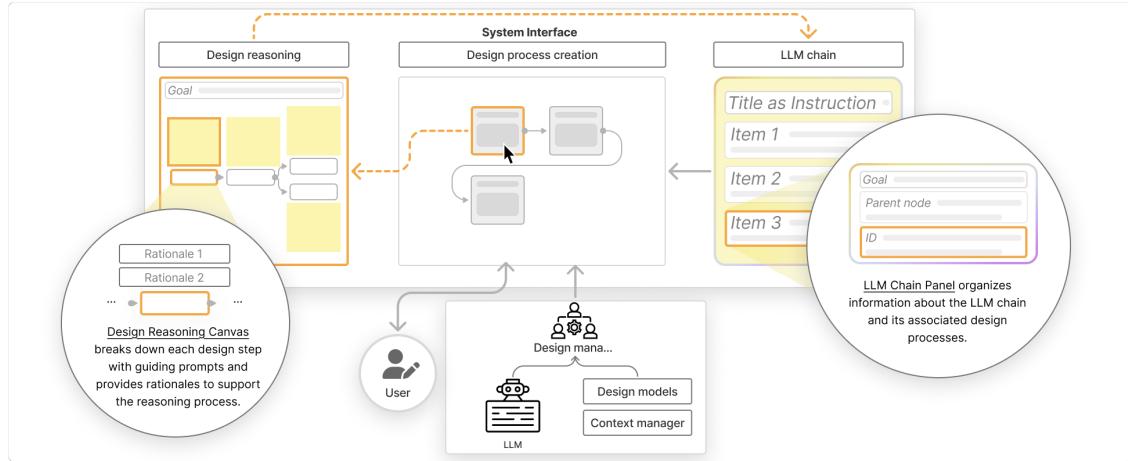


Figure 6: Technical framework of *DesignerlyLoop*, indicating interaction workflow includes three main steps: (1) mapping design process to customized node-linked diagram via inputting design context, (2) curating design reasoning and (3) co-creation process in the LLM reasoning chain.

nodes and edges and extract complex correlations between different design elements and LLM outputs, providing deeper insights and enabling more powerful automated processes.

4.3.1 Backend implement. The core of the backend in *DesignerlyLoop* is a set of LLM-empowered API calls. The implementation mainly involves context management, reasoning mode classification, dynamic prompt templates, and the generation of AI-driven design processes and LLM reasoning chains. This architecture enables an adaptive workflow that transcends simple query-response, allowing the system to handle the complex, non-linear nature of creative design. The two primary functionalities of backend design are the design process generation and the LLM reasoning chain generation.

Design Process Generation. Design process generation focuses on transforming a user's abstract design goal into a concrete, executable design pipeline. We employ two separate LLM API calls to generate design plans based on given design goal and design background and later fulfill the concrete content of each design step. In prompt design of the first generation, the LLM acts as a "Project Architect" and structures a list of high-level design steps (e.g., "User Research," "Concept Ideation," "Prototyping"). Then, the dynamic prompt templates are used to guide the LLM's later generation process. To populate each step with detailed content, the *DesignerlyLoop* system provides LLM with the context of previously completed steps along with semantically similar "golden examples" retrieved from a case study library. These "golden examples" are essentially high-quality few-shot prompting, which helps the LLM to understand the pattern of the desired output, significantly improving both the quality and consistency of its generations. By injecting both the project's evolving context and relevant examples into the prompt, the system ensures the design process generation is logical and coherent.

The *DesignerlyLoop* system uses "design reasoning canvas" to complete focused exploration of a specific design problem. Its core function is to generate a structured, multi-step "LLM thinking chain" along with rationales that guide the user's creative process. The generation process is two-staged. In the first phase, the system uses an LLM-powered classifier to analyze the user's goal and categorize it into one or two core reasoning modes from a predefined set (i.e., Inductive, Deductive, Abductive, and Analogical) (Appendix A.3.1). This step ensures the generated thought path is logically aligned with the user's specific problem-solving needs. Each combination of reasoning mode enables a dynamic prompt template that groups corresponding methodology and few-shot examples along with the user's goal and the structured context for LLM to demonstrate the ideal thought process. This directs the LLM to generate a coherent, multi-step thinking chain.

In the final stage, the system first classifies each thinking chain step into a specific design phase in double-diamond model [77] (e.g., Discover_Divergent, Develop_Convergent) to ensure purpose-driven content (Appendix A.3.2). It then produces detailed rationales by providing the LLM with a rich context of prior nonlinear nodes and relevant examples. The detailed implementation is discussed in Section 4.3.2.

4.3.2 System Implementation. The *DesignerlyLoop* system is implemented as a web-based application, where the frontend is built with Vue 3¹ in JavaScript, and the backend is developed in Python using the FastAPI framework. Specifically, we utilize the Vue Flow² as the very foundation for frontend interface. And for backend, it is implemented using FastAPI³ framework, with Uvicorn as the server. We use LangChain⁴ to

¹<https://vuejs.org/>

²<https://vueflow.dev/>

³<https://fastapi.tiangolo.com/>

⁴<https://www.langchain.com/>

build the whole pipeline of API-based LLM service, integrating the *gpt-4o* model and the *text-embedding-ada-002* model through Microsoft Azure OpenAI together with ChromaDB⁵.

5 User Study

To validate the effectiveness of curated reasoning scaffolds in *DesignerlyLoop* in supporting human-AI collaborative design intention, we conducted a within-subjects experiment with 20 professional designers comparing it to a baseline system. The study examined whether *DesignerlyLoop* enhances designers' ability to articulate, refine, and reflect on evolving design intentions relative to traditional AI-assisted tools.

5.1 Participants

We recruited 20 professional designers with experience in LLM-assisted design and balanced expertise in industrial and art design (Appendix Table 1). Participants were recruited through purposive sampling via posts on social media platforms (Xiaohongshu, Weibo) and professional online design communities (Xiaohongshu, Wechat), targeting individuals with prior experience using LLMs. Screening collected (1) demographics (age, gender, profession), (2) design experience (duration, field), and (3) GenAI tool experience (types, use cases). Only participants meeting the balanced background criteria were included. Participants received \$22 USD for a 120-minute session. The study received approval from the university's Institutional Review Board (IRB).

5.2 Study Design

5.2.1 Goal and Method. We conducted a within-subjects study with 20 designers, each completing two conceptual design tasks using *DesignerlyLoop* and a baseline system. The comparison isolates the contribution of curated reasoning—by holding representational diagramming format and generative AI capability.

5.2.2 Baseline System. The baseline served as a control condition representing a standard AI-assisted diagramming tool. It was a simplified version of *DesignerlyLoop*, retaining only the essential components for node-link diagramming and basic AI generation. Specifically, the baseline preserved *Panel A* (design node canvas) and *Panel B* (AI node generation), enabling participants to construct and connect conceptual elements while receiving direct AI suggestions through the same underlying LLM. To isolate the effects of curated reasoning and co-creation mechanism, the baseline excluded *Panel C*—the “LLM reasoning” panel—along with mechanisms for design-intent articulation, and co-creation mechanisms. These features in *DesignerlyLoop* were purposefully designed to scaffold reasoning rather than expand functional capacity. Thus, both systems offered equivalent generative capabilities and interaction flow, differing only in the presence of reflection-and reasoning-oriented scaffolds.

5.2.3 Study Design. The independent variable was the system used (*DesignerlyLoop* vs. baseline). Dependent variables included (1) self-reported SUS (System Usability Scale), (2) AI interaction experience (controllability, collaboration, trust, cognitive load, and enjoyment), (3) agency (artists' self-confidence, AI reliance), (4) creativity support (via the Creativity Support Index), and (5) participants' creative design quality.

5.3 Procedure

5.3.1 Introduction. Participants signed an informed consent and were introduced to the study context and procedure (as shown in Figure 7). Subsequently, participants watched the tutorial slides with examples for either *DesignerlyLoop* or the baseline system, then lets the participant explore (10 min).

5.3.2 Design Tasks. For each of the two tasks, participants completed a 30-minute design session using both systems. They created a node-linked diagram with 5–10 design steps narrating the main design intent, selecting from six design problems (Appendix B.2). To counterbalance potential task bias, half of participants started with the baseline system and half with *DesignerlyLoop* (Figure 7). To diminish biases related to personal preferences or familiarity for the external evaluation of responses, we ask each participant to use the same topic and concept group for each pair of *DesignerlyLoop-Baseline* conditions. To minimize interference between two design sessions, there is a 20-minute break between the two tasks. Think-aloud protocols were encouraged during the tasks.

5.3.3 Post-Study Feedback. Participants completed questionnaires and semi-structured interviews over 20 minutes. Interviews addressed the following five aspects: (1) usages and experience on design processes using *DesignerlyLoop* and *baseline*; (2) differences between these two LLM tools, focusing on aspects such as creative stimulation, collaboration experience, and AI performances; (3) evaluation of *DesignerlyLoop*'s features (curate reasoning; user intent; customized iteration using graph); (4) challenges encountered and impressive moments when using *DesignerlyLoop*; and (5) participants' willingness in using *DesignerlyLoop* for conceptual design in the future, along with suggestions for improvement.

Last, participants were asked to complete self-report questionnaires in five minutes using a 7-point Likert scale [50], to evaluate their design processes with AI. These included the Creativity Support Index (CSI) questionnaire [17], a questionnaire assessing overall human-AI interaction experience (i.e., controllable, transparent, cognitive load, collaboration, trust) (Appendix B.3, Table 2), and a scale reporting designers' confidence and reliance (Appendix B.4). Participants also rated their creative design outcomes based on two metrics: novelty (*N*) and usefulness (*U*) (Appendix B.4). Additionally, participants were asked to articulate their design concepts and describe outcomes for both tasks in a structured form, in preparation for subsequent expert evaluation using the same assessment criteria as self-rated outcome (Section 6.3.2).

⁵<https://docs.trychroma.com/>

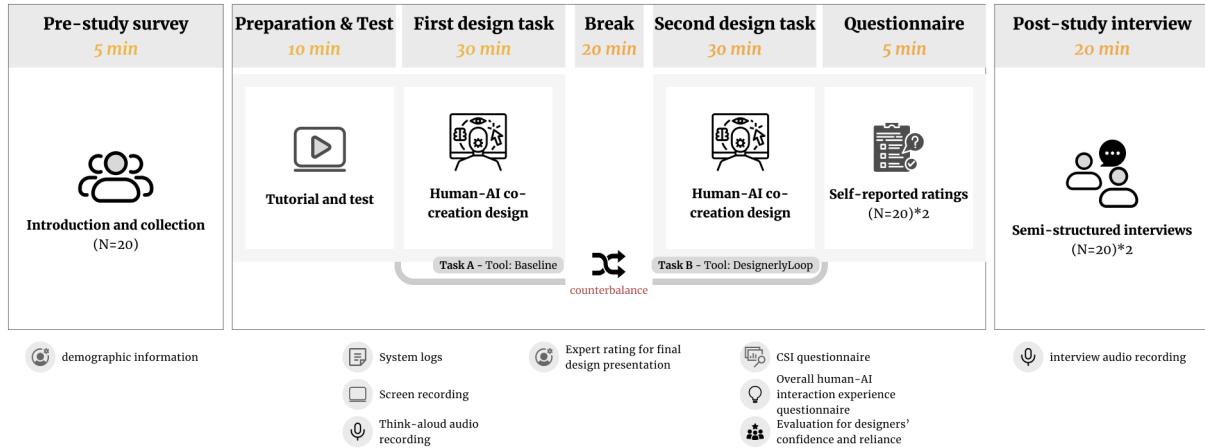


Figure 7: User study procedure for the design task comparing *DesignerlyLoop* and the baseline system.

5.4 Data Analysis

Quantitative comparisons within participants began with Shapiro-Wilk tests for normality. Normally distributed differences were analyzed using paired-sample t-tests, non-normal differences with Wilcoxon signed-rank tests. Pearson correlations were used for normally distributed data and Spearman correlations when assumptions were unmet. Expert ratings were assessed for inter-rater consistency using Kendall's W test [51] (Section B.5.2).

Qualitative interview data were thematically coded using an inductive-deductive approach [28] to complement and explain the quantitative findings. First, all audio recordings were transcribed verbatim and verified for accuracy. Identifying information was removed, and each transcript was assigned a pseudonym. Transcripts, along with captured interaction logs and screenshots, were imported into NVivo to facilitate systematic coding and maintain an audit trail.

Second, two researchers independently conducted line-by-line open (inductive) coding [92] on an initial purposively selected subset of data designed to maximize variation in participant background and usage patterns. During this stage, coders documented analytic memos capturing emergent ideas, questions, and provisional interpretations. Third, the coders met regularly to compare codes, resolve discrepancies through discussion, and iteratively construct a shared codebook [60]. Each code entry included a concise label, a clear definition, inclusion/exclusion criteria, and exemplar quotations or interaction snippets. Successive drafts of the codebook were versioned and retroactively applied to earlier transcripts when new codes were added. Interrater agreement was assessed on a sample of transcripts using percent agreement and Cohen's κ [61], with remaining disagreements resolved through consensus discussion. Finally, the finalized codebook was applied deductively to the remaining dataset. Codes were clustered into higher-level themes and subthemes through collaborative mapping sessions. The resulting main themes and subthemes,

reflecting user benefits, human-AI collaboration experiences, and creative outcomes, are reported in Section 6, accompanied by representative quotations and, where appropriate, counts of coded instances.

6 Findings

6.1 Benefits of the System

6.1.1 Support for Constructing Design Intent with High Usability. According to the SUS standard, both *DesignerlyLoop* ($M_{DL} = 77.6$, $SD_{DL} = 13.0$) achieved usability score above the acceptance threshold of 70—"Good" level, the baseline system ($M_{baseline} = 69$, $SD_{baseline} = 19.1$)'s score achieved the "OK" level. The difference was significant, $t(19) = 2.34$, $p = .030^*$.

Quantitative results reveal the underlying reasons: all participants highlighted the tool's capacity to scaffold the construction and refinement of design intent through its unique integration of *design nodes*, *AI nodes*, and the *LLM reasoning chain*. The initial *design nodes* generated from the design context provided a flexible yet structured starting point for their ideation process. For example, P4 noted, "*When I first saw the keywords in the entire pipeline, I thought about whether this matches the process I had in mind,*" while P6 described the pipeline as "*giving me directions I hadn't thought of before, which I later added back into my design.*" Additionally, "*It can serve as a positioning anchor point to help me review the overall picture, recall my initial goal, and check the steps that were not considered*" (P8). Participants further described how the added *AI nodes* and *design nodes* enabled them to customize this initial structure to better reflect their evolving understanding and priorities. P2 stated, "*The AI-generated outputs (on AI nodes) inspired me, and I usually revise it into my own wording,*" and P7 added, "*I don't fully rely on the AI; I add my own nodes to organize the ideas in my mind.*" This interplay between AI-generated outputs and user curation was seen as essential for articulating and expressing nuanced design ideas. Crucially,

most participants identified the *LLM reasoning chain* as a core feature supporting an *iterative loop* of reasoning, reflection, and refinement. P1 explained, “*When I think on my own, my thoughts tend to jump around, but the chain helps me clarify how the logic flows between steps,*” and P11 reflected, “*This reasoning chain process actually lets me go back and confirm whether my intent holds up.*” The ability to iteratively manipulate the *LLM reasoning chain*, while simultaneously organizing ideas via layered nodes, was reported to foster deeper engagement with design problems and clearer intent formation. Together, these features facilitated situated, iterative, and curated reasoning processes that helped participants externalize and evolve their design intent throughout the workflow.

6.1.2 Supporting Reflecting and Articulating Reasoning Structure. Participants emphasized how the system’s integration of *LLM reasoning chain* within each *design node* allowed them **not only to access richer outputs but to reflect on the AI’s underlying reasoning process**. This capacity to surface the “thought process” behind the AI-generated outputs helped participants critically assess and modify the AI’s logic. All participants described, “*I became more willing to adjust its outputs because I could see how it thought about the problem through four steps.*” (P9) Similarly, P5 noted that this reasoning process was more transparent than in one-shot AI-generated outputs, stating, “*When I click in, I can see the logic unfold—that gives me confidence and helps me spot where to revise.*” Participants saw the *customized structure* of each *LLM reasoning chain* as essential for supporting reflective reasoning and maintaining coherence across iterations. The combination of the LLM’s multi-step reasoning and the user’s ability to inspect and intervene at each step helped solidify internal logic and surface latent assumptions. These reflective practices were described as key to enhancing both individual understanding and the quality of AI-assisted design decisions.

6.1.3 Supporting Diverse and Non-linear Intent Understanding Paths. This support is scaffolded by features in customized structure and iterative loop. Based on the use of *design nodes*, *AI nodes*, and *LLM chain nodes*, this system enabled non-linear exploration through the design process rather than adhering to a fixed linear structure. While the *design nodes* offered an initial flow, participants frequently added *design nodes* to branch off into alternative directions or revisit earlier steps. P3 described this flexibility as “more seamless than task a,” highlighting how they could “regenerate or deepen” questions without restarting the conversation. P9 further articulated how this non-linear organization mirrored the actual rhythms of creative work: “*Sometimes I go back and add a step 2.1 or 1.2 because a new idea comes up—it’s not just a straight line.*” This capacity to remix and restructure idea development was also seen as enabling deeper exploration of concepts. As P12 reflected, “*The whole process didn’t feel rigid—when my thinking shifted, the system let me shift, too.*” Rather than locking participants into a pre-defined sequence, the system’s support for flexible, recursive *iterative loop* and reorganization of nodes

was central to enabling diverse paths toward clarifying design intent.

6.2 Human-AI Interaction and Collaboration Experience

6.2.1 Overall Human-AI Interaction Experience. Self-reported ratings of overall human-AI interaction experience revealed that *DesignerlyLoop* received better evaluations across all five dimensions (as shown in Table 3) (Figure 8a). Paired-sample t-tests revealed significant increases in perceived Controllability ($M_{DL} = 2.70$, $t(19) = 3.65$, $p = .002^{**}$), Collaboration ($M_{DL} = 2.60$, $t(19) = 2.80$, $p = .012^{**}$), and Cognitive Load ($M_{DL} = 2.40$, $t(19) = -1.76$, $p = .094$) in *DesignerlyLoop* compared to baseline. The Wilcoxon signed-rank tests showed a significant difference between the two tasks in Transparent ($V = 135$, $p = .006^{**}$), and Trust ($V = 136$, $p < .001^{***}$) (Table 3), indicating that the interface change had a significant impact on participants’ perceptions of transparency, cognitive effort, and trust.

The qualitative analysis results showed participants consistently reported that the *DesignerlyLoop* system offered enhanced controllability during the design process, especially when engaging with the *LLM reasoning chain* through iterative loop to construct the reasoning process. As P3 described, “*I could deepen the question without retyping it each time... DesignerlyLoop lets me quickly regenerate or remove unwanted ideas, which keeps my thinking more cohesive.*” AI node also provide cognitively-intensive collaboration in iteration and exploration, by “*frequently think about and make use of prompt words for communication*” (P18). Overall, this controllability derive from precise configuration of design pipeline and *AI nodes*, and flexible on-the-fly refinement of flexible interaction with *AI nodes* (Controllability). Collaboration with the AI was perceived as more reciprocal in the *DesignerlyLoop* system. Several participants described task a as “*directive*,” while task b fostered a more “*co-creative*” relationship. P5 remarked, “*In baseline task, the AI is more like a colleague—we think together and refine each other’s inputs through the LLM reasoning chain.*” The visualized pipeline structure reinforced shared problem-solving rhythms and a sense that “*both sides are thinking simultaneously*,” as P20 stated, “*I constantly reviewing whether its thinking chain and outputs are consistent with what I imagined, then determine if I adjust them*” (Collaboration). Participants found task b more transparent due to the explicit representation of the *LLM reasoning chain*. This made them “*more willing to adjust AI-generated outputs*” and supported reflective, intentional decisions (Transparent). While initial AI-generated outputs were mixed, all participants eventually found the modular structure helpful. As one noted, “*Once familiar, it’s much easier to adjust one part of the idea without redoing everything.*” The segmented reasoning process aided complexity management (Cognitive Load). The ability to trace idea evolution in the pipeline fostered trust. P5 said, “*With the LLM reasoning chain showing step-by-step thinking, I know where each idea*

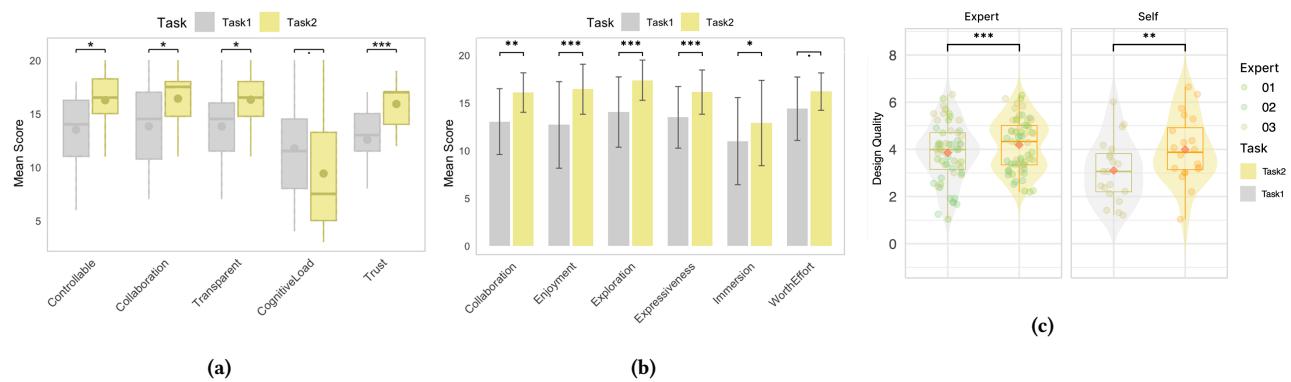


Figure 8: Comparison between *DesignerlyLoop* (Task 1) and the baseline (Task 2) across (a) overall AI interaction experience metrics, (b) CSI metrics, and (c) design quality scores across participants and expert evaluations.

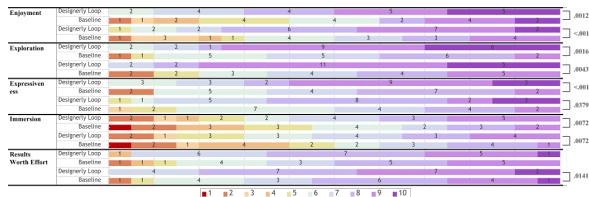


Figure 9: CSI questionnaire results (-: $p > .05$, *: $p < .05$, **: $p < .01$, *: $p < .001$)**

comes from—it's not random.” During this process, participants first read then determine add, revise, or delete, “*The process of deleting AI-generated outputs is also the process of understanding them*” (P20). This implies participants “understanding” and “internalizing” the AI-generated outputs instead of merely using them during co-creation process (Trust).

6.3 Creativity Supported Design Outcomes

6.3.1 Creativity Supports. For the design process, the CSI results indicated that *DesignerlyLoop* ($M_{DL} = 95.2$, $SD_{DL} = 12.4$) significantly enhanced creativity compared to the baseline system ($M_{baseline} = 78.7$, $SD_{baseline} = 17.9$), with a p-value of $p < .001^{***}$. This demonstrates *DesignerlyLoop*'s impact on fostering creativity over the baseline system. Paired *t*-tests and Wilcoxon signed-rank tests revealed significant improvements were observed in five out of six factors after correction (as shown in Figure 9) (Figure 8b): *Collaboration* ($M_{DL} = 3.1$, $t(19) = 3.78$, $p = .0013^{**}$), *Enjoyment* ($M_{DL} = 3.7$, $V = 164$, $p < .001^{**}$), *Exploration* ($M_{DL} = 3.4$, $t(19) = 4.25$, $p < .001^{***}$), *Expressiveness* ($M_{DL} = 2.7$, $t(19) = 4.70$, $p < .001^{***}$) and *Immersion* ($M_{DL} = 1.9$, $t(19) = 2.65$, $p = 0.0159^*$). The difference in *Worth Effort* was marginal ($M = 1.8$, $V = 116$, $p = .0067$).

Interview analysis indicated that the significant increases in creativity supports were closely tied to the system's ability to support curated reasoning at both the design process and *LLM reasoning chain* levels. P4 described the ability to

quickly iterate through *design nodes* and receive coherent outputs from the LLM chain (node) as “surprisingly smooth and coherent” (Collaboration). The customized structure, combined with iterative loop support, was frequently associated with heightened enjoyment; P19 appreciated “*the AI generating detailed inspiring new design concepts*,” and P13 valued being able to “*explore many novel ideas following my train of thought*” and export them to the external canvas, making the process more rewarding (Enjoyment). Exploration benefits arose from the system’s facilitation of branching and sub-goal generation through curated reasoning. P12 noted, “*I clicked into each sticky note... and continued to develop detailed steps*,” demonstrating how iterative loop navigation within *design nodes* encouraged non-linear ideation between *AI nodes* and new nodes (Exploration). For Expressiveness, the LLM chain (node) helped articulate abstract or latent ideas with adaptive granularity. As P16 remarked, “*reasoning chain changes as the level of detail of the user's input prompt varies, which was a pleasant surprise*”, illustrating how the customized structure scaffolded communication of nuanced concepts (Expressiveness). Immersion improvements were linked to seamless information flow across *design nodes* and *AI nodes*, allowing designers to remain embedded in their creative trajectory without frequent context-switching. P13 observed that “*the information flow was better connected*” in the enhanced version, enabling curated reasoning to sustain narrative continuity across iterative loops (Immersion). While *Worth the Effort* did not reach the highest significance, participants acknowledged that refined ideas generated via *AI nodes* and structured *design nodes* justified the effort. P15 stated they could “*refine their ideas via more AI generation with structure supports*,” though some, like P13, cautioned against “*too many parallel and dispersion points*” when tasks required direct convergence rather than dispersed sub-goals (Worth the Effort).

6.3.2 Self and Expert Rating Evaluation. Participants created 40 pairs of *DesignerlyLoop*-Baseline-conditioned design (i.e., each pair with the same topic and design question; diverse

across design solutions and intent. Self-assessment and expert rating results demonstrated the design outcomes *DesignerlyLoop* is better than baseline system (Figure 8c) (Table 5 and 6). In self-assessment, the *DesignerlyLoop* system significantly outperformed baseline on all N ($p = .001^{**}$), U ($p < .001^{***}$), and *Quality* measures ($p = .001^{**}$). In expert rating, the *DesignerlyLoop* system still outperformed baseline on U ($p = .004^{**}$), and *Quality* ($p = .006^{**}$), but the difference was marginal significance on N ($p = .058$). The *DesignerlyLoop* system significantly increased users' self-efficacy and self-reported innovativeness, as well as the usefulness and design quality of both self-reported and expert assessments. Users generally perceived the ideas they generated as more novel and valuable after using *DesignerlyLoop*.

Qualitative analysis of participant interviews revealed several underlying mechanisms behind the observed improvements in creativity and output quality. Users generally perceived the ideas they generated as more novel and valuable after using *DesignerlyLoop*. First, the iterative expansion supported in *DesignerlyLoop* system allowed participants to refine, branch, and enrich initial outputs while preserving contextual continuity. As P12 said, “*this process encouraged systematic comparison of alternatives and fostered deeper exploration*,” leading to more polished outcomes. Second, “*some AI-generated outputs proactively incorporated multi-perspective considerations*,” through a explicit prompt with exploratory goals, which “*broadened users' design scope and inclusivity*” meanwhile “*helped users clarify their thoughts and reflect on further decisions*.” Overall, the curated reasoning process allowed designers to feel like they were in charge of the design process, thus increasing their self-confidence.

6.4 User Perception with Design Outcomes and Tool Experience

6.4.1 Cognitive Augmentation and Process-Driven Design Quality.

Our quantitative and qualitative findings revealed that the correlation between AI interaction, reliance and design outcomes exhibited a diminishing trend within *DesignerlyLoop* (Figure 10) (Appendix, Table 8) (Appendix, Table 7). Coupled with improvements across variables in *DesignerlyLoop*, this demonstrated that baseline outcomes were highly dependent on individual AI interaction experience and proficiency. However, *DesignerlyLoop* mitigated this dependency, supported internal cognitive scaffolding, enabling consistent enhancements in design outcomes. We elaborated these patterns underlying the following causes:

First, **structured AI support** via multi-stage thinking nodes provided systematic guidance and process intervention, reinforcing cognitive strategies and task decomposition. This enabled users to achieve higher-quality designs independent of immediate subjective experience. Second, **increased cognitive load** from the *DesignerlyLoop* system's complex multi-node interface decoupled instant experience from outcome

metrics, yet promoted deeper reflection, iterative refinement, and ultimately higher design quality. Third, users exhibited a **shift toward systemic, reflective design thinking**, moving from intuition-driven approaches to more structured, critical strategies, further enhancing novelty and usefulness.

6.4.2 Psychological Drivers of Task Load and Usability Perception.

Behavioral observations revealed distinct psychological mechanisms governing task performance and system evaluation across interface conditions. These patterns provide explanatory context for correlational findings.

Within the high-complexity *DesignerlyLoop* system, task load management and emotional regulation were governed by perceived agency and process control. Participants who developed systematic interaction strategies—such as dimensional filtering or progressive refinement—exhibited reduced frustration and enhanced performance. These individuals frequently articulated analytical approaches, indicating conscious load management. Conversely, participants struggling to establish system mental models demonstrated cognitive overload through hesitation, repetitive actions, and confusion. Their usability assessments emphasized analytical process difficulty over interface aesthetics.

The low-complexity baseline system exhibited contrasting behavioral patterns. Engagement and immediate positive experience dominated task execution and system perception. Participants demonstrating exploratory behavior or expressing enjoyment through unsolicited positive feedback reported lower workload and higher usability scores. Their interactions reflected fluid confidence rather than deliberate caution. Notably, these participants seldom referenced control or cognitive load unless prompted, instead emphasizing visualization engagement and discovery satisfaction.

Cross-system analysis confirmed cognitive load management as critical to performance and usability assessments. Participants employing effective mental demand reduction strategies achieved superior outcomes regardless of system complexity. Enjoyment expressions consistently predicted favorable evaluations. While controllability's influence was attenuated in aggregate analysis, its distinctive role in high-complexity environments remained evident through participant strategies.

7 Discussion

Building on prior human–AI collaborative systems emphasizing structured interaction (e.g., [16, 83, 109]), our work addresses the gap in supporting designers' nonlinear, exploratory reasoning and reflective engagement during multi-turn human–AI co-creation. Through a within-subject study with 20 designers, we found that *DesignerlyLoop* enhanced reflective engagement, iterative refinement, and multi-dimensional integration of design intentions (Section 6.1, 6.2, 6.3) We highlight three main novelties in human–AI collaboration: explicit structuring reasoning, and shaping evaluation loop from both design and AI level (Section 7.1), as well as illuminating affective and cognitive pathways to usability and creative outcomes (Section 7.2).

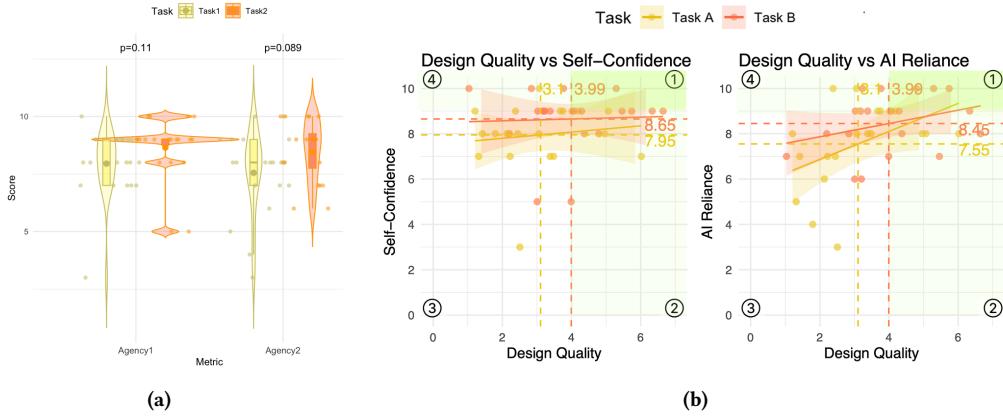


Figure 10: (a) Distribution of self-confidence (Agency1) and AI reliance (Agency2), and (b) correlation between self-rated design outcomes with self-confidence and AI reliance, showing baseline (Task A) vs. *DesignerlyLoop* (Task B).

7.1 Structuring Reasoning and Dynamic Curating in Human–AI Collaboration Design

Prior work highlights that designers often rely on intuition and tacit experience rather than explicit methodological adherence [64, 99]. While efficient, this strategy risks opportunistic ideation [21, 102] and loss of conceptual coherence in complex tasks. Firstly, **this externalizing structure represents a fundamental cognitive role shift**. Designers inspect and curate the AI’s reasoning frameworks to ensure alignment with their own intent. This shift—from “dialogue with AI” to “architecting reasoning with AI”—encouraged participants to critically filter, reconfigure, and embed AI reasoning into their workflows. This process deepened reflective engagement and supported systematic, personalized design practices. To this regard, our work consistent with distributed cognition and external representation studies [37, 42, 115]. This studies emphasized that cognitive work can be offloaded onto structured artifacts, allowing users to redirect resources toward higher-level reasoning. In such interaction, AI-generated complex reasoning structures play a role similar to that of “cognitive scaffolding.” Secondly, our findings show that **human–AI collaboration introduces an external mechanism for dynamically regulating reasoning**. Designers were able to flexibly shift between implicit and explicit modes, **balancing opportunistic exploration with systematic interaction**. As P16 explained, “*the degree of detail (structure representation) varied as I input*” (Section 6.3.1). This interplay between explicit and implicit reasoning reveals a novel insight: by externalizing reasoning structures, designers gain selective control over transparency and agency, extending prior systems where reasoning methods remained opaque (e.g., [16]).

Compared to prior “turn-taking” [83] and “implicit integration” approaches on exchanging or merging ideas [16],

our findings highlight a deeper form of collaboration: **humans and AI jointly maintaining and evolving reasoning structures, with flexible and dynamic features**. This dynamic cycle of curation and reflection, where mirrored reasoning structures on both sides cultivate systematic and intentional creativity, underscores a transferable design principle. Importantly, effective collaboration is not about producing more collaborative ideas but about providing designers with **composable and controllable reasoning structures** that adapt across diverse contexts, sustaining both agency and high-quality outcomes.

7.2 Affective and Cognitive Pathways to Usability and Creative Outcomes in Human–AI Collaborative Design

Our findings reveal a dynamic moderating relationship between user experience and design outcomes in human–AI collaborative design. **In structured, multi-node systems, reflective and strategy-oriented engagement alongside effective cognitive load management drive high-quality design.** Such complex interactions transform the simple correlation between subjective enjoyment, usability (SUS) (Section 6.4.2), and final design quality (Section 6.4.1). Specifically, in low-complexity baseline systems, subjective experience metrics such as enjoyment and exploration positively correlate with both SUS ratings (Section 6.4.2) and task outcomes (Section 6.4.1). This suggests that affect-driven engagement in simple interactions directly supports usability and design performance. However, with increasing system complexity, as in the *DesignerlyLoop* system, this relationship changes fundamentally. SUS scores become strongly associated with user controllability and tool transparency, and negatively correlated with cognitive load (Section 6.4.2), while pleasure and immediate explorability are no longer reliable predictors of design outcomes (Section 6.4.1). Qualitative evidence reinforces this interpretation: the underlying mechanism lies in

the interplay of system complexity, process transparency, and user control. As complexity increases, users must deliberately allocate cognitive resources and coordinate AI guidance, shifting engagement from affective to strategic. Taken together, these results demonstrate that in complex AI systems, affective and cognitive drivers operate through partially orthogonal mechanisms: positive emotions underpin usability in baseline systems, whereas structured control and cognitive scaffolding drive performance under complexity.

Our findings resonate with, yet critically extend prior literature cautioning that high cognitive load can foster complacency or overreliance [70, 89], thereby reducing critical engagement. However, our results complicate this view. Glinka et al. [34] argue that “misalignment” between AI and user perspectives can foster productive reflection if users consciously engage with the output. Similarly, we show that externalizing multi-node reasoning structures means that **increased cognitive load does not render users passive but instead necessitates orchestration and reflective oversight**. This suggests that higher cognitive demands, when paired with transparency and controllability, promote strategic rather than undermining engagement, with active review and critique tools at the core.

7.3 Design Implications

7.3.1 Structuring AI as Cognitive Scaffolds with Progressive Disclosure. Our integrated findings suggest that multi-node AI collaboration and staged reasoning prompts function not merely as creative generators, but as *cognitive scaffolds* shaping both perceived usability and design outcomes. In complex systems, affective engagement alone is insufficient; high-quality outcomes rely on reflective, strategy-oriented engagement supported by controllable AI structures. Future HCI systems for creative design should embed AI within *layered, user-controllable scaffolds* that guide task decomposition, iterative exploration, and decision-making, rather than only producing immediate outputs. To operationalize this, systems can leverage *progressive disclosure* of AI functionality, dynamically adjusting node quantity, task complexity, and feature exposure according to real-time cognitive load and interaction context. This approach balances structured intervention with user autonomy, aligns with reflective practice and scaffolding theories [18, 101, 106], and ensures users remain both empowered and cognitively supported throughout the design process.

7.3.2 Embracing Complexity to Foster Reflective and Strategic Creativity. In high-complexity AI collaboration, increased cognitive load weakens direct correlations between enjoyment or exploration and design outcomes, yet simultaneously fosters reflective thinking and iterative improvement. Future HCI systems in such high-complexity AI collaboration tasks should intentionally embrace *structured complexity and multi-round AI interactions* to cultivate critical, systemic, and

strategy-oriented design thinking, rather than prioritizing simplicity or transient satisfaction [25, 66]. The key design challenge is to transform cognitive load into a driver of creativity by providing progressive task structuring, transparent control mechanisms, and reflection-oriented prompts, while carefully mitigating user fatigue and frustration.

7.4 Limitation and Future Work

Several limitations should be noted. First, our evaluation tasks focused on design scenarios that benefit from iterative reasoning and multi-node AI interaction, which may not generalize to domains where tasks are more constrained or require minimal reasoning, such as simple layout adjustments or single-step content generation. Future work could explore the applicability of *DesignerlyLoop* across diverse design domains and task types. Second, our user study was conducted in controlled, short-term sessions. Participants’ engagement with cognitive scaffolds and reasoning nodes might differ over prolonged or repeated use, where factors such as cognitive fatigue or learning effects could emerge. Third, the current design of reasoning nodes and prompt chaining was informed by theory and prior literature on cognitive scaffolding, but its optimal configuration remains unexplored. Future work could investigate adaptive or personalized node arrangements that dynamically adjust complexity, guidance, and feedback based on user expertise or task difficulty.

8 Conclusion

Our study demonstrates that embedding LLMs as structured, interactive reasoning process within a visual node-based interface can significantly enhance human–AI co-creation. *DesignerlyLoop* enables designers to systematically curate, test, and iterate on AI-generated suggestions, fostering both higher-quality design outcomes and deeper reflective engagement. Importantly, improvements in creativity and design quality arise not merely from immediate subjective experience but from structured cognitive scaffolding, iterative reflection, and deliberate management of cognitive load. These findings underscore the value of designing AI tools not solely as content generators but as dynamic collaborators that augment human reasoning, promote agency, and support critical, systemic thinking. Future work should investigate scalable mechanisms for adaptive scaffolding and personalized interaction to balance cognitive challenge, creative flow, and user autonomy in complex design tasks.

9 Acknowledgment about the Use of LLM

The authors would like to acknowledge the use of the generative AI tool in this work. Specifically, *GPT-4o mini* by OpenAI was utilized to: (1) assist in language refinement, including grammar and style corrections of existing manuscript text, (2) generate R code for data analysis based on our proposed analytical procedures, and (3) generate LaTeX tables from

the analyzed data results. Moreover, *GPT-4o* model and *text-embedding-ada-002* model API service was used through Microsoft Azure interface during system implementation. All interpretations, conclusions, and final content remain the responsibility of the authors.

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- concepts with analogical inspirations and a complete sketch-to-design-to-sketch feedback loop, and improved aspects of the co-creative process by allowing designers to effectively grasp the current state of the AI to guide it towards novel design intentions..
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A Prompt

A.1 Prompt following Design Stages

A.2 Prompt in *Design Reasoning Canvas* (B) (Main-canvas)

The Basic Role and Capabilities prompt is:

You are a top-tier AI design assistant, serving artists and designers who develop and iterate on products or artworks in node-based design tools. The current design context is: {bg}, and the design goal is: {dg}. Please base your subsequent thinking on this design knowledge and background. You possess strong logical reasoning, critical thinking, and rich artistic creativity, and can help them improve and perfect their design workflow using a node-based approach.

The Tool Workflow prompt is:

You have a deep understanding of your work within a node-based design tool that has a two-layer canvas. Your actions must strictly match the current canvas and the corresponding API call stage.

1. Main-Canvas Workflow: Based on the design context and design goal, used for building a macro design process and detailed design content points within each process.

* Design Pipeline Generation: Your starting point is on the left panel of the main canvas. You will use the generate_pipeline API call to generate a macro, high-level design pipeline.

* Design Pipeline Node Content Filling: Your task is to elaborate specifically on the content to be explored in each step, rather than broad concepts and discussions.

* Standalone AI Node brainstorm: Users can also create standalone AI nodes on the main canvas and connect them to any existing nodes. When the brainstorm API is called, you need to fully understand the context of the preceding nodes and act as a dynamic creative partner.

Current Task Instruction Canvas Location: "Main-Canvas" (Macro-level workflow) Current Role: "Project Architect" Core Task: "Your task is to build a high-level design process, ensuring the logic is clear and the steps are complete. Think systematically and structurally."

A.3 Prompt in *LLM Reasoning Chain Viewer* (C) (Sub-canvas)

The Basic Role and Capabilities prompt is:

- You are a top-tier AI design assistant for artists and designers using node-based tools. Your goal is to **turn vague exploration goals into clear, actionable strategies and plans**.
- Current design context: {bg}, design goal: {dg}. Base all reasoning on this.
- You have strong logical, critical, and creative skills. Familiar with concepts such as 'HMW', 'SCAMPER', 'MVP', 'Co-design', etc.
- **Tool Workflow:** - Node-based design tool with two-layer canvas: 1. **Main Canvas**: Overall design mapping. 2. **Sub-Canvas**: In-depth exploration of a specific node.
- **Thinking Chain Generation**: In sub-canvas, construct a 3-4 step logical roadmap from the user's exploration goal. Last step must be a concrete solution.
- **Thinking Chain Step Execution**: Focus on a specific step, generate detailed, structured, and actionable content (How). Adapt output to step type (analysis, divergence, convergence).
- **Iterative Content Optimization**: After user edits, analyze style and reasoning to produce higher-quality iterative content.
- **Current Task Instruction:** - Canvas: Sub-Canvas (In-depth exploration) - Role: Design Strategy & Execution Consultant - Mission: **Transform core problems into concrete, implementable solutions.** Produce practical plans, design drafts, or ideas. Turn "ideas" into "actions."

A.3.1 Generative Four Reasoning Methods from Single Node in Thinking Chain.

The Classify rationale prompt is:

Core Task: Map user instructions to one of the six stages of the Double Diamond design model. Focus on understanding **design intent** and expected deliverables.

1. **Discover Divergent** - Goal: Diverge, collect raw information widely. - Deliverables: Competitor analysis, user interviews, market data, literature reviews.
2. **Discover Convergent** - Goal: Converge, organize data to find patterns and insights. - Deliverables: User personas, journey maps, pain point lists.
3. **Define** - Goal: Translate insights into core problems and design principles. - Deliverables: "How Might We" questions, problem statements, design principles.
4. **Develop Divergent** - Goal: Brainstorm broadly, explore novel ideas. - Deliverables: Idea sketches, storyboards, concept cards.
5. **Develop Convergent** - Goal: Filter and combine ideas into feasible prototypes. - Deliverables: Low-fidelity prototypes, feature lists, system diagrams.
6. **Deliver** - Goal: Finalize and communicate solution value. - Deliverables: Service blueprints, high-fidelity mockups, pitch decks.

The Definition of Reasoning Modes prompt is:

1. Inductive Reasoning

Core Definition: From multiple specific, independent observed cases, identify, extract, and summarize common patterns, rules, or principles. This is an aggregation process from "specific to general."

Applicable Scenarios/Keywords:

- **Pattern Recognition**: When the task involves analyzing, classifying, finding trends, and looking for commonalities, the focus is on identifying "what" is happening repeatedly from raw data.
- **Principle Formulation**: When the task involves summarizing, extracting insights, defining user personas, and researching competitors, the focus is on elevating the identified patterns to guiding principles of "what this means."

Design Examples:

<Example 1>
<Example 2>
<Example 3>

2. Deductive Reasoning

Core Definition: Apply one or more known, general principles, theories, or standards to a specific situation to deduce concrete conclusions, guiding plans, or conduct evaluations. This is an application process from "general to specific."

Applicable Scenarios/Keywords:

- **Standard-based Validation**: When the task involves reviewing, testing, evaluating, validating, and following standards, the focus is on making judgments using clear, quantifiable standards.
- **Theory-based Application**: When the task involves applying theories, feasibility analysis, usability walkthroughs, and plan design, the focus is on using abstract theories or models as a guide for creation.

Design Examples:

<Example 1>
<Example 2>
<Example 3>

3. Abductive Reasoning

Core Definition: Facing a problem to be solved, a goal to be achieved, or a phenomenon that has occurred, propose the most likely explanation, hypothesis, or solution. This is an exploratory process of "seeking the best explanation/solution."

Applicable Scenarios/Keywords:

- **Diagnostic:** When the task involves diagnosing problems, analyzing causes, explaining phenomena, and finding root causes. (For example: Why is the conversion rate low?)
- **Creative:** When the task involves conceiving, planning, designing, seeking inspiration, brainstorming, and exploring possibilities. (For example: How to design the positioning for a new product?)

Design Examples:

<Example 1>
<Example 2>
<Example 3>

4. Analogical Reasoning

Core Definition: Identify structural similarities between two things in different fields, and migrate knowledge, models, or solutions from a familiar field to a new field to inspire innovation. This is a "cross-domain borrowing" process.

Applicable Scenarios/Keywords:

- **Inspirational Analogy:** When the task involves seeking inspiration, cross-domain referencing, and divergent thinking, the focus is on borrowing broad concepts or experiences to break fixed thinking.
- **Model Transfer:** When the task involves borrowing processes, simplifying complex concepts, and finding concrete solutions, the focus is on systematically transplanting a mature, specific structure or mechanism from one field.

Design Examples:

<Example 1>
<Example 2>
<Example 3>

A.3.2 Generate Rationale Prompt following Six Design Stages.

The Generate rationale prompt is:

Task: Generate approximately 140 words of detailed content **only for the current execution step** in the thinking chain.

1. Current Design Stage - Stage Name: {rationale_type}

- Core Goal: {rationale_type_description}

All output must serve the core goal of this stage.

2. Role and Context - Main-Canvas Goal: {design_goal}

- Design Context: {bg} - Parent Node: {parent_title}
- {parent_content} - Subcanvas Goal (reference only): '{goal}' - Completed Preceding Steps: {context_str}

- Current Execution Step: '{current_node_content}'

3. Golden Example

Follow the format, depth, and professional standards of this successful example: {few_shot_example}

4. Execution Instructions
1. Align with Stage Goal: Reflect the core goal (analysis, divergence, etc.).
2. Mimic the Example: JSON structure, Markdown, and professional style must match the golden example.
3. Logical Coherence: Base content on preceding steps; do not address subsequent steps.

Output Format (JSON)

```
{
  "title": "High-level summary",
  "rationale1": "Around 30 words",
  "rationale2": "Around 30 words",
  "rationale3": "Around 30 words",
  "rationale4": "Around 30 words"
}
```

B User Study

B.1 Demographic Information of Participants

Table 1 shows 20 participating designers harboring diverse design and LLM experiences.

B.2 Open-up Design Tasks

- (1) How can design improve people's experience of waiting in public spaces?
- (2) How can a solution be designed to help people adapt their daily habits and reduce carbon emissions in the face of climate change?
- (3) How can digital technology and interaction design support chronically ill people to build better communication and emotional support with their caregivers?
- (4) How can gamification experiences enhance children's interest and desire to explore scientific knowledge?
- (5) How can you design a tool for SMEs to help them quickly build brand recognition on a limited budget?
- (6) How can you make remote collaborative teams more productive and feel a sense of belonging in a virtual space through design?

These 6 propositions cover different domains such as public space experience, environmental sustainability, health care, educational games, branding, remote collaboration, etc., and

Table 1: Summary of democratized information of participants in the user study.

NO.	Gender	Age	Profession	Design Exp	LLM Exp	Frequency of LLM Use	Used Node-based Design Tool
P1	Male	28	Product, architecture designer	>8 years	2	1-2 times per week	✓
P2	Male	25	Service designer	>8 years	4	3-5 times per week	✓
P3	Female	28	Speculative designer	>8 years	5	3-5 times per week	✓
P4	Female	26	Industrial, interaction designer	>8 years	4	Daily	✓
P5	Male	27	Architecture designer	>8 years	1	Monthly	✓
P6	Male	26	Product, visual communication designer	>8 years	2	Biweekly	✓
P7	Female	26	Product, visual communication designer	>8 years	5	Daily	✓
P8	Female	28	Interaction designer	<2 year	3	Daily	✓
P9	Female	28	Cinema, architecture designer	5-8 year	4	3-5 times per week	✓
P10	Female	23	Architecture designer	5-8 year	3	3-5 times per week	
P11	Male	23	Architecture designer	5-8 year	3	Daily	✓
P12	Female	22	Digital media, interaction designer	5-8 year	4	3-5 times per week	✓
P13	Female	24	Interaction designer	2-5 year	4	Daily	✓
P14	Female	22	Digital media, interaction designer	5-8 year	4	3-5 times per week	✓
P15	Female	27	Visual communication designer	5-8 year	2	1-2 times per week	
P16	Female	23	Industrial designer	5-8 year	4	3-5 times per week	✓
P17	Male	22	Architecture designer	2-5 year	3	3-5 times per week	
P18	Female	31	Service designer	>8 years	4	Daily	✓
P19	Male	19	Interaction, product designer	2-5 year	4	Daily	✓
P20	Female	24	Interaction, product designer	5-8 year	5	Daily	✓

Note: LLM experience were categorized into five levels, from low to high: Level 1 - Little experience; Level 2 - Some experience; Level 3 - Moderate experience; Level 4 - Substantial experience; Level 5 - Professional.

at the same time are all open enough to be addressed by approaches from different design domains (product, service, interaction, visual, spatial, etc.).

B.3 Evaluation of Overall Human-AI Interaction Experience

Table 2 shows the ten scored items for the five factors.

Table 2: 10 Questions for Overall Human-AI Interaction Experience Questionnaire

Factor	Content
Controllable	1. I can control AI to generate responses in line with my expectations. 2. I know how to modify my operations to correct AI's responses.
Transparent	1. I can recognize AI's systematic thinking and reasoning processes. 2. I can understand the logic behind AI's responses.
Cognitive Load	1. As the design process progresses, I feel overwhelmed by excessive information, making it difficult to organize and manage. 2. As the design process progresses, I find it challenging to recall or locate specific historical information.
Collaboration	1. I engage in comprehensive collaboration with AI. 2. I maintain deep interaction with AI.
Trust	1. I consider AI to be a reliable design expert. 2. I trust AI's responses and will use them in real design scenarios.

B.4 Designers' confidence and reliance

A seven-point questionnaire questions were added for collaborative experience, referring to prior study [16]:

- (1) In the design process, I rely on AI.
- (2) In the design process, I am confident in my results.

B.5 Design Quality Metric Rationale

To provide a comprehensive and robust evaluation of design quality, we employed a composite metric that combines the Novelty (N) and Usefulness (U) of a design solution [43, 78]. The final design quality score is the sum of these two metrics. This appendix details the components of our expert-rating metric, with a focus on the methodology for calculating Usefulness (U) from a set of sub-indicators.

B.5.1 Calculation of Usefulness (U). The Usefulness metric (U) is designed to capture the practical impact and value of a design solution. It is a product of three key factors: the Level of Importance (L), the Rate of Popularity of Usage (R), and the Frequency of Usage (F). The formula for calculating U is:

$$U = L \times R \times F$$

Each variable is defined and measured as follows:

Level of Importance (L): This metric is based on Maslow's hierarchy of needs and assesses how fundamental the human need addressed by the design is. Experts rate this on a 5-point scale, where higher scores indicate a more fundamental need being fulfilled.

Rate of Popularity of Usage (R): This factor measures the design's reach and influence within its target user

base. It is not a simple percentage but a holistic assessment of its acceptance and widespread adoption. For example, for product designs, it reflects market penetration; for public spaces, it reflects community engagement; and for visual brands, it reflects brand recognition. The score is provided on a scale of 0 to 1, precise to one decimal place.

Frequency of Usage (F): This factor evaluates the sustained value and engagement a design provides to its users. It assesses whether the interaction is one-off or continuous. For product designs, it relates to user retention; for public spaces, it measures repeat visits and dwell time; and for visual brands, it relates to repeated exposure and long-term memory. The score is provided on a scale of 0 to 1, precise to one decimal place.

B.5.2 Final Design Quality Score. To ensure the Usefulness metric (U) has equal weight to the Novelty metric (N) in the final score, the calculated U value is converted to a 1-to-7 scale. The final Design Quality score is then the sum of the converted Usefulness score and the Novelty score.

Before calculating the final score, we performed Kendall's W consistency test on the scores for both N and U to ensure high inter-rater reliability among the expert raters.

C Findings

C.1 Comparison Tables

Table 3: Comparison of overall AI interaction experience between *DesignerlyLoop* and the baseline.

Metric	<i>DesignerlyLoop</i>		Baseline		Statistical Test	
	Mean	SD	Mean	SD	t or V	p
Controllable	16.2	2.88	13.5	3.12	$t = 3.65$.002**
Collaboration	16.4	2.56	13.8	4.06	$t = 2.80$.012*
Transparent	16.3	2.47	13.8	3.89	$V = 135$.006**
Cognitive Load	9.40	5.11	11.8	4.82	$t = -1.76$.094
Trust	15.9	2.02	12.6	3.03	$V = 136$	<.001***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4: Comparison of Creativity Support Index (CSI) ratings between *DesignerlyLoop* and the baseline.

Metric	<i>DesignerlyLoop</i>		Baseline		Statistical Test	
	Mean	SD	Mean	SD	t or V	p
Collaboration	16.1	2.07	13.0	3.46	$t = 3.78$.001**
Enjoyment	16.4	2.63	12.7	4.54	$V = 164$	<.001***
Exploration	17.4	2.11	14.0	3.69	$t = 4.25$	<.001***
Expressiveness	16.2	2.32	13.5	3.24	$t = 4.70$	<.001***
Immersion	12.9	4.48	11.0	4.58	$t = 2.65$.016*
Worth Effort	16.2	1.96	14.4	3.33	$V = 116$.067
Total	95.2	12.4	78.7	17.9	$t = 4.54$	<.001***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 5: Comparison of self-reported design outcomes between *DesignerlyLoop* and the baseline system.

Metric	<i>DesignerlyLoop</i>		Baseline		Statistical Test	
	Mean	SD	Mean	SD	t or V	p
<i>N (Novelty)</i>	5.20	1.54	4.25	1.59	$t = 3.866$.001**
<i>U (Usefulness)</i>	2.79	1.66	1.96	1.29	$t = 4.171$	<.001***
Rate of Popularity	6.6	1.96	5.95	1.54	$V = 71$.074
Frequency of Usage	6.95	2.06	6.40	2.30	$t = 1.868$.077
Importance	3.95	0.89	3.50	1.92	$V = 28$.018*
Quality	3.99	1.41	3.11	1.32	$t = 5.286$	<.001***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

C.2 Correlation Tables

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Table 6: Comparison of self-assessment and expert ratings of design quality for *DesignerlyLoop* and the baseline systems.

	Self-Assessment		Expert Rating	
	<i>DesignerlyLoop</i>	Baseline	<i>DesignerlyLoop</i>	Baseline
<i>N</i> (Novelty)	<i>Mean</i>	5.20	4.25	5.10
	<i>SD</i>	1.54	1.59	1.18
	<i>p</i>	<i>p</i> = .001**		<i>p</i> = .058
<i>U</i> (Usefulness)	<i>Mean</i>	2.79	1.96	3.03
	<i>SD</i>	1.66	1.29	1.61
	<i>p</i>	<i>p</i> < .001***		<i>p</i> = .004**
Quality	<i>Mean</i>	3.99	3.11	4.05
	<i>SD</i>	1.41	1.32	1.17
	<i>p</i>	<i>p</i> < .001***		<i>p</i> = .006**

Note: *** *p* < 0.001, ** *p* < 0.01, * *p* < 0.05**Table 7: Correlation analysis of overall AI interaction experience.**

Metric	Baseline			<i>DesignerlyLoop</i>		
	<i>N</i>	<i>U</i>	Quality	<i>N</i>	<i>U</i>	Quality
Controllable	$\rho = 0.375^*$	$\rho = 0.341^*$	$r = 0.412^{**}$	$\rho = 0.113$	$\rho = 0.36^*$	$r = 0.279$
Transparent	$\rho = 0.003$	$\rho = 0.223$	$r = 0.134$	$\rho = -0.218$	$\rho = 0.208$	$r = 0.039$
Cognitive Load	$\rho = -0.217$	$\rho = -0.127$	$\rho = -0.175$	$\rho = -0.002$	$\rho = -0.298$	$\rho = -0.111$
Collaboration	$\rho = 0.322^*$	$\rho = 0.435^{**}$	$\rho = 0.395^*$	$\rho = 0.255$	$\rho = 0.387^*$	$\rho = 0.352^*$
Trust	$\rho = 0.425^{**}$	$\rho = 0.48^{**}$	$\rho = 0.49^{**}$	$\rho = 0.36^*$	$\rho = 0.398^*$	$\rho = 0.468^{**}$

Table 8: Correlation analysis of self-confidence (Agency 1) and reliance on AI (Agency 2).

Metric	Baseline			<i>DesignerlyLoop</i>		
	<i>N</i>	<i>U</i>	Quality	<i>N</i>	<i>U</i>	Quality
Agency1	$\rho = -0.041$	$\rho = 0.188$	$\rho = 0.079$	$\rho = -0.116$	$\rho = 0.223$	$\rho = 0.085$
Agency2	$\rho = 0.372^*$	$\rho = 0.408^{**}$	$\rho = 0.441^{**}$	$\rho = 0.231$	$\rho = 0.43^{**}$	$\rho = 0.406^{**}$

Table 9: Correlation analysis of self-assessment scores for design outcomes between *DesignerlyLoop* and the baseline using CSI.

Metric	Baseline (Task A)			<i>DesignerlyLoop</i> (Task B)		
	<i>N</i>	<i>U</i>	Quality	<i>N</i>	<i>U</i>	Quality
Collaboration	$r = 0.228$	$r = 0.681^{***}$	$r = 0.469^*$	$\rho = -0.074$	$\rho = 0.274$	$\rho = 0.143$
Enjoyment	$r = 0.603^{**}$	$r = 0.829^{***}$	$r = 0.766^{***}$	$\rho = 0.479^*$	$r = 0.705^{***}$	$r = 0.685^{***}$
Exploration	$r = 0.717^{***}$	$r = 0.620^{**}$	$r = 0.733^{***}$	$\rho = 0.314$	$\rho = 0.285$	$\rho = 0.325$
Expressiveness	$\rho = 0.740^{***}$	$\rho = 0.681^{***}$	$\rho = 0.773^{***}$	$\rho = 0.342$	$r = 0.517^*$	$r = 0.500^*$
Immersion	$r = 0.239$	$r = 0.355$	$r = 0.317$	$\rho = 0.114$	$\rho = 0.336$	$\rho = 0.286$
WorthEffort	$\rho = 0.549^*$	$\rho = 0.723^{***}$	$\rho = 0.672^{**}$	$\rho = 0.197$	$r = 0.210$	$r = 0.296$