"It's Not About Doing Less Thinking, It's About Thinking Differently": Cognitive Redistribution in Human-AI Co-Creative Systems

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Abstract

This paper examines how AI assistance across different content types (visual, textual, code/structural) transforms cognitive processes in knowledge work environments. Through a qualitative study with varying professional backgrounds, this case study investigates how creative practitioners redistribute cognitive engagement when using AI-enhanced whiteboarding tools. Through semi-structured interviews and reflexive thematic analysis, three main themes were identified: (1) Task-Based Agency Delegation, (2) Content Type Trade-offs, and (3) Evolution of Intention and Evaluation. Preliminary findings suggest that traditional models of higher-order thinking are being reshaped as professionals reconceptualize their cognitive roles rather than simply reducing cognitive load, developing strategies to maintain cognitive sovereignty while leveraging AI capabilities. Rather than simply automating tasks, AI prompts a redistribution of cognition where human engagement shifts from implementation to direction and from detail evaluation to system evaluation. This preliminary research contributes to enhancing theoretical frameworks for understanding the complex dynamics of human-AI collaboration and provides practical design recommendations for creativity support tools that preserve agency while enhancing collaborative potential.

Keywords

Human-AI co-creativity, Cognitive redistribution, Epistemic interfaces, Creative agency, Cognitive Sovereignty, AI-enhanced design tools

1. Introduction

The integration of AI into creative knowledge work environments has introduced significant changes in how individuals approach cognitive tasks. This research focuses specifically on creative work "designing" that requires both convergent (i.e., analytical, solution-focused) and divergent thinking (i.e., generative, idea-oriented) [1, 2]. While early research focused on AI performing specific sub-tasks with an emphasis on automation, we are witnessing a shift toward synergistic systems where human decision making and creativity are augmented in human-AI collaboration, leveraging their complementary abilities [3, 4]. Despite this progress, current approaches are system-centric, lacking comprehensive frameworks for understanding how the quality of human experience and cognitive processes transform across different types of

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tasks and abstraction levels. This human-centered perspective is crucial to ensure long-term fulfillment and well-being in increasingly AI-mediated work environments [5, 6].

Whiteboarding tools or digital collaborative platforms where users can create visual diagrams, organize textual information, sketch interfaces, and develop prototypes in a shared workspace present a rich context for studying these transformations. These tools support the externalization of thinking, facilitating facilitate real-time human-AI co-creation and idea development. Unlike expert systems designed for specific applications, whiteboarding environments support the full spectrum of knowledge actions from ideation to implementation in various modes of expression, providing a window into how AI assistance might differentially impact cognitive processes across representation types (i.e., from visual sketching and textual organization to structural coding) [7]. In addition, it has been suggested that the agency in the interaction between humans and AI should not be conceptualized as a static human attribute but as an emergent property that arises from interactions between professionals, tools and contexts [8]. This perspective moves beyond viewing agency as merely a matter of control or autonomy, recognizing instead the dynamic, contextual nature of creative agency in increasingly AI-mediated environments [9]. Building on these works, the current case study examined how creative practitioners experience and use AI-enhanced whiteboarding tools, particularly focusing on their perceived benefits and barriers in maintaining creative agency.

2. Related Work

2.1. Dynamic Cognitive Models for Human-AI Creative Collaboration

Traditional cognitive models employ hierarchical frameworks, distinguishing between "lower" and "higher" order thinking activities [10, 11]. These taxonomies categorize cognitive activities into applying, analyzing, evaluating, and creating as progressively higher-level functions. Similarly, creativity research differentiates between convergent and divergent thinking processes, providing complementary creative directions [12, 2]. However, these models inadequately capture the complex dynamics of cognitive processes in AI-assisted creative work, leaving significant gaps in our understanding of which cognitive activities should be prioritized in expert skill development. Design thinking approaches, with their emphasis on iterative and non-linear progression (Figure1) [13, 14], potentially offer more appropriate frameworks for conceptualising human-AI creative collaboration, but their empirical validation in AI-augmented environments remains limited.

2.2. Content Types and Abstraction Levels

What makes the understanding or cognitive engagement in AI-assisted environments more complicated is different modes of representation (visual, textual, code/structural) that represent distinct ways of encoding and manipulating information [15], which provide a useful framework for understanding parallel approaches to expressing ideas rather than hierarchical levels. On the other hand, true hierarchical degrees of concreteness/abstraction within any given content type [16] may become significant as they can represent transition points where cognitive challenges occur and where AI assistance may be most valuable. While research on whiteboard

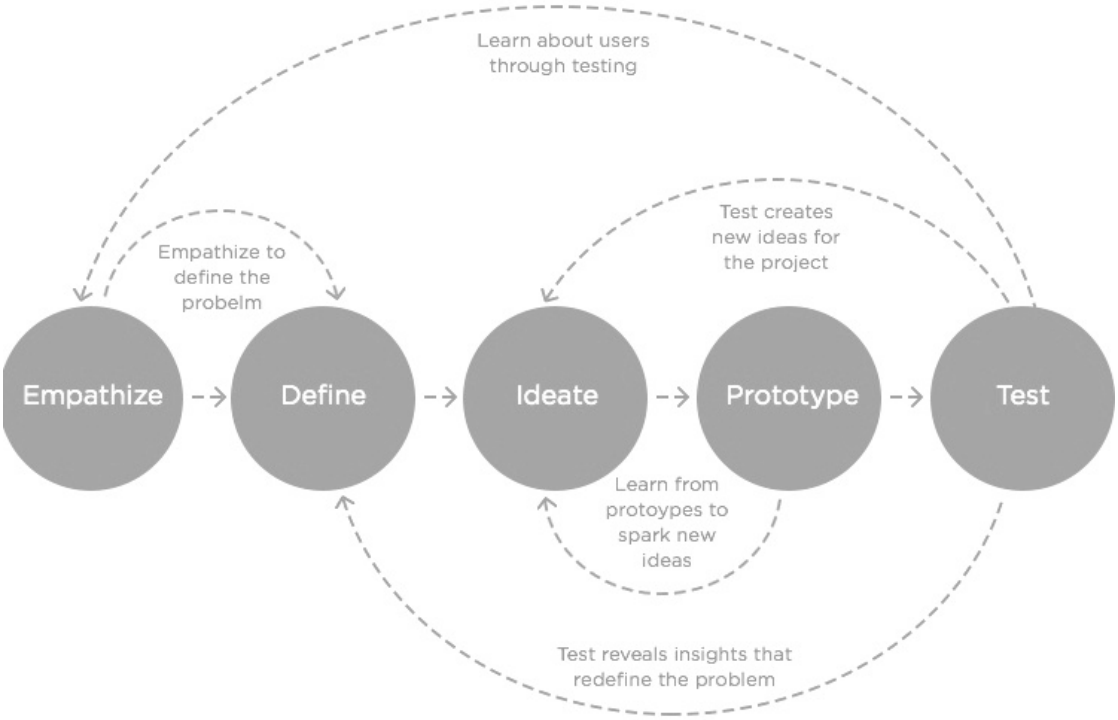

Figure 1: Dynamic, Non-linear Process of Design Thinking, adopted from [13].

use demonstrates how these environments naturally support movement between abstraction levels [17], they rarely address the integration of generative AI into these tools.

2.3. Agency Negotiation and Professional Identity

Another key factor in human-AI collaboration is agency, the sense of control and ownership over one's actions and their results [18], which affects a wider range of outcomes: professional well-being and identity, including eudaimonic well-being [19], creative fulfillment [20], and professional identity development [21]. Recent theorists propose that agency is co-constructed and context-dependent, varying as users engage differently with AI features across situations [8, 22]. However, traditional approaches to evaluating AI whiteboarding tools often narrowly focus on user satisfaction or perceived control [23] and need to be expanded to account for the active, adaptive nature of AI systems that can shape human thinking and creative processes [24]. This study adopts a cognitive offloading model rather than strong Extended Mind Theory [25] with participants consistently maintaining authority over goal-setting and creative direction while strategically distributing implementation tasks to AI systems. Thus, the research conceptualizes human-AI collaboration as strategic delegation where human agency is preserved while recognizing transformative effects of AI assistance on cognitive processes.

Table 1
Participant demographics

Participant	Occupation	Current Whiteboarding Tool use
P1	MSc Student	Brainstorming, explaining concepts, and prototyping
P2	MSc Student	Group collaboration and information organization
P3	Digital designer	Brainstorming with minimal AI experience
P4	Visual artist	Limited digital whiteboarding experience
P5	Artist/Lecturer/Designer	Diagramming and design

3. Method

This qualitative study was guided by three primary research questions:

1. Agency Across Content Types: How do users' experiences of agency change across different content types (visual, textual, code/structural) in whiteboarding tools?
2. Interaction Patterns: What patterns emerge when users negotiate agency with AI at transition points between content types?
3. Professional Impact: How does AI assistance at different content types affect users' creative fulfillment and professional identity?

3.1. Data Collection

For rich, contextualised understandings of how creative professionals negotiate their relationship with AI across different modes of expression, this study employed semi-structured interviews with five participants representing different professional backgrounds with experiences in AI-assisted design practices. (Table 1). The semi-structured interviews lasted between 45-60 minutes and explored participants' experiences with AI-enhanced whiteboarding tools, focusing on their interactions with different content types, their strategies for evaluating AI outputs, and their perceptions of agency and creativity. Visual prompts showing different types of AI assistance across abstraction levels were used to facilitate discussion.

3.2. Data Analysis

Case study employed reflexive thematic analysis[26] to analyze interview data. This methodological approach allowed for identifying patterns across participants while maintaining sensitivity to subjective and contextual nature of their experiences. The analysis process involved familiarization with data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing analysis.

4. Findings

Analysis revealed three main themes related to how AI transforms cognitive processes across content types in whiteboarding environments: (1) Task-Based Agency Delegation, (2) Content Type Trade-offs, and (3) Evolution of Intention and Evaluation.

4.1. Task-Based Agency Delegation

Participants described strategies for maintaining creative agency while leveraging AI capabilities. Rather than delegating based on traditional hierarchies of "higher" versus "lower" cognitive processes, participants made delegation decisions based on task requirements, personal preferences, and professional identity.

4.1.1. Concept Ownership

All participants emphasized maintaining ownership over core concepts and creative direction. P3 explicitly stated: *"The idea/concept is mine. AI is a tool just like a camera or paint."* P5 noted: *"I always begin with my own concept, even if it's rough. I never ask AI to generate the initial idea."* This concept ownership served as a fundamental boundary across all content types, positioning AI as an implementation assistant.

4.1.2. Process Control

Participants maintained control through strategic AI engagement at specific workflow points. P2 described using AI *"more in the later stages"* of the design process, while P1 depicted an iterative approach:*"I take AI output, change it, and put it back in again."* This process control was particularly evident at transition points between content types, reflecting what has been identified as the balance between sketching control and AI implementation [24]. P4 described maintaining control specifically at these moments: *"When I'm moving from a sketch to more structured elements, that's when I'm most careful about how I use AI. Those transitions are where you can lose control of your vision."*

4.1.3. Verification Authority

All participants maintained final evaluative authority over AI outputs. P4 described developing *"healthy gut feelings"* for assessing AI suggestions, while P2 emphasized that they would *"always write the questions first"* before consulting AI. This verification authority was manifested differently across content types: more focused on aesthetic judgment at visual levels and more on functional effectiveness at code levels. By positioning themselves as the final evaluator of quality and appropriateness, participants preserved their professional role even as they incorporated AI assistance.

4.2. Content Type Trade-offs

Analysis revealed distinct patterns of human-AI collaboration across different content types, each with unique trade-offs influencing participants' engagement strategies.

4.2.1. Visual Content: Stylistic Control vs. Efficiency

At the visual level, participants navigated trade-offs between efficiency and stylistic control, exploration and precision, and personalization versus convention. For example, P2 valued the potential efficiency of AI for visual refinement: *"It would be so nice if AI could do it for you... I*

would save so much time." However, P5 expressed concerns about aesthetic control: *"I do not find [AI] aesthetic very attractive and control over the images is really poor."* Participants were generally comfortable with AI assistance for standardized elements and refinement tasks, but maintained stronger control over stylistic and conceptual aspects of visual work. P1 appreciated not having to *"draw elements that were like already widely available,"* while still maintaining creative direction. This shows specific criteria for AI delegation that may help them navigate identified trade-offs. P2 further demonstrated active decision-making when she explained: *"I would only use it for brainstorming ideas... I wouldn't use AI to make a final prototype design because I would be very worried that it's stealing other people's work."*

4.2.2. Textual Content: Originality vs. Assistance

At the textual level, participants balanced originality against efficiency, ownership against assistance, and personal voice against standardization. For example, P1 articulated concern about homogenization of expression: *"Are we all going to become this kind of average person? Where you and I end up having the same thoughts about a particular topic."* However, participants also described their systematic approach to resolve the tension between human creativity and AI assistance, as demonstrated by P3 (*"I may ask AI to give me an initial list of ideas to start with and then develop or add my own."*) and P2 (*"First of all, I write down all of my own ideas and use my own brain and creativity, and then I do AI as well, just as an extra tool just to come up with some extra ideas."*)

4.2.3. Code/Structural Content: Learning vs. Productivity

At the code/structural level, participants weighed understanding against efficiency, skill development against productivity, and agency against implementation speed. P3 explicitly articulated this tension: *"Immense time saving when coding"* while worrying: *"I'm less good at coding as a result since I don't have to commit so much to memory."* Participants showed the highest comfort with AI delegation with this content type, with P2 expressing strong interest in visual-to-code translation: *"I would definitely use the graphic to AI prototype option."* However, this delegation came with concerns about dependency and deskilling, reflecting what has been described as the tension between immediate benefits and long-term skill development [27]. P1 demonstrated how they would navigate this conflict by maintaining learning goals alongside productivity: *"I can feed it like a bunch of data about something and then go, 'Can you tell me three or four interesting points about this user data set?' For example, 'what age group are they, what are the top problems they have, are there any patterns in terms of their demographics.'"*

4.3. Evolution of Intention and Evaluation

Findings revealed evolution in how participants approach intention and evaluation when working with AI across content types.

4.3.1. From Implementation Intention to Directorial Intention

Participants described shifts from implementation-focused to direction-focused work. P3 explicitly described this directorial approach: *"I'm directing the work and AI is helping me realise it."* P5 also noted: *"I'm thinking more about the overall direction and less about exactly how each element should be executed."* , suggesting a need for new skills in articulating intentions in ways that guide AI implementation effectively. Specifically, P1 described developing systematic approaches: *"It's not about doing less thinking, it's about thinking differently. I think it teaches you to be a bit more self-reflective. So you start working on something and then you're like, 'Yeah, this is going to be great.' And then you present it [to the AI] and it'll say, 'Well, what about this? What if this happens?' and then you go, 'Oh, I never considered that.'"* , representing not a reduction in cognitive load but a reorientation of cognitive engagement: from hands-on implementation to strategic direction.

4.3.2. From Detail to System Evaluation

Similarly, participants' evaluative focus shifted from assessing individual implementation details to evaluating system-level outcomes and holistic results. P1 described becoming *"more structured"* in their approach and developing *"a more careful and structured way"* of executing projects. Rather than scrutinizing every implementation detail, participants focused more on whether the overall outcome aligned with their creative vision. P5 noted: *"I'm developing new ways of judging success. It's less about perfection in execution and more about whether the whole thing works together."* , reflecting the evolution from micro-level to macro-level evaluative thinking, requiring new evaluative frameworks focusing on conceptual alignment and systemic effectiveness.

5. Discussion

5.1. Epistemic Interfaces and Cognitive Sovereignty

Preliminary findings suggest that AI-enhanced whiteboarding tools function as "epistemic interfaces", environments that not only support outcome of knowledge work but actively reshape how knowledge is created, represented, and evaluated [28]. As static interfaces evolve into dynamic and interactive knowledge generation environments, fundamental questions arise about how we preserve creative agency and cognitive sovereignty: the capacity to maintain meaningful control over one's thinking processes and creative identity in increasingly AI-mediated environments [29]. Participants demonstrated consistent efforts to preserve sovereignty through concept ownership, process control, and verification authority. Further, the greater comfort with AI assistance with the code/structural type challenges traditional hierarchies that place implementation as "lower" than ideation, suggesting instead that structural implementation requires its own expertise and careful consideration regarding delegation strategies. These patterns of findings challenge simplistic narratives about AI either enhancing or diminishing human capability, instead suggesting cognitive redistribution where human thought processes are redirected toward more conceptual, directorial, and evaluative functions, reflecting what

has been described as the development of expert mental representations and metacognitive skills for tool use [30, 31].

5.2. AI-enhanced Design Tools Supporting Creative Professionals

The concerns participants expressed about homogenization, dependency, and skill atrophy point to broader social implications of AI in knowledge work. Further, content types differences in AI delegation also raise questions about how professional identities and skills may evolve differently across disciplines [9]. Visual artists expressed more concern about aesthetic homogenization, while those focused on structural implementation worried more about deskilling. Effective AI whiteboarding tools must therefore support: intentional direction, meaningful evaluation, identity preservation, and capability expansion [27]. Based on these findings, this study proposes design recommendations for AI-enhanced whiteboarding tools (Table 2).

5.3. Transferable Implications

While the current study focused on whiteboarding environments, these findings have implications for AI integration across various creative and knowledge work tools. The patterns of content-type preferences, agency negotiation, and evolution of intention and evaluation likely extend to other contexts where AI assists creative work [22]. The redistribution of cognitive engagement this study observed, from implementation to direction, from detail to system evaluation, represents a broader pattern that may characterize human-AI collaboration across domains [32]. This cognitive shift aligns with observations of a "performance-metacognition disconnect" in human-AI collaboration [33], where participants must develop new metacognitive strategies to effectively direct AI systems even as their direct implementation skills may change. The evolution from detail to system evaluation represents a form of meta-evaluation, requiring users to develop new frameworks for assessing AI outputs in terms of overall coherence rather than implementation accuracy [34]. This suggests a need for research and design approaches that explicitly support this cognitive redistribution rather than simply automating existing tasks [33]. Design tools should recognize and facilitate the emerging role of humans as creative directors while providing appropriate scaffolding for the new evaluative skills required in AI-augmented workflows.

5.4. Limitations and Future Work

While this case study provides valuable insights into how AI transforms cognitive processes in whiteboarding environments, several limitations should be acknowledged. The findings should be considered preliminary and exploratory, requiring validation through larger-scale studies across more diverse domains, task difficulties, and professional contexts. Additionally, the mechanisms of how cognitive engagement is redistributed require further empirical validation. Future research could explore how this concept relates to existing frameworks like distributed cognition[35] and extended mind theory [25], while developing more specific operational definitions and measurement approaches for quantitative follow-up. Longitudinal studies would be particularly valuable for understanding how AI-human cognitive partnership and professional adaptation evolve over time.

Table 2
Design Recommendations for AI-enhanced Whiteboarting Tools

Theme		Recommendation Details
Content-Type Sensitive Interfaces	Design AI assistance acknowledging different user preferences across content types	Visual tools should emphasize refinement over generation; textual tools should support organization while maintaining authorship; code tools should provide automation with clear explanations.
Professional Identity Support	Align features with diverse professional needs	Efficiency for technical users, variation and inspiration for creatives, collaborative support for team-based work.
Agency-Preserving Controls	Provide mechanisms supporting cognitive sovereignty	Human-in-loop workflows, transparency about AI contributions, and framing AI as suggestions rather than replacements.
Transition Support	Provide control at content type transitions	Design explicit support for human oversight when moving between visual, textual, and structural representations.

6. Conclusion

This exploratory research reveals that AI is not simply automating existing cognitive processes but transforming how creative knowledge workers distribute cognitive engagement across different types of creative tasks. The traditional hierarchy of "higher" and "lower" order thinking is being replaced bya more complex distribution where humans maintain creative agency and evaluative authority while delegating implementation details across varying content types. Participants' engagement with AI in whiteboarding contexts is driven by complex needs related to creative identity, capability expansion, and cognitive sovereignty. The shift from implementation-focused to direction-focused creative work represents a transformation in how creative practitioners conceptualize their roles and identities. Individuals are developing sophisticated strategies for maintaining cognitive sovereignty while leveraging AI capabilities, focusing on intention and evaluation rather than implementation as the core of their creative identity. This suggests the need for whiteboarding tools that support this evolving cognitive synergy rather than simply automating existing tasks. By understanding these emerging patterns of human-AI cognitive collaboration, we can design tools that better support the redistribution of cognition while preserving human agency and creative fulfillment. The future of AI-enhanced knowledge work lies not in replacing human thinking but in creating new cognitive synergy that expands what humans can create and understand.

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Declaration on Generative AI

The author used ChatGPT-4.5 for formatting. After using this tool, the author reviewed and edited the content as needed and took full responsibility for the publication's content.

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