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Artificial Intelligence–Mediated Creativity in Collaborative Design Teams

Dr. Isabella M. Carter

Associate Professor, University of Amsterdam, Netherlands

Abstract

Generative artificial intelligence is altering collaborative design by introducing computational agents directly into ideation, visualization, critique, iteration, and concept-development activities that were previously distributed primarily among human team members. AI-mediated design collaboration can accelerate the generation of alternatives, provide rapid visual or textual stimuli, reduce repetitive production work, and help less experienced designers engage more productively in early-stage ideation. The same capabilities can create creative convergence, automation bias, weakened psychological ownership, premature fixation on polished AI outputs, and reduced participation when AI becomes the dominant source of ideas. Recent experimental evidence shows that human–AI co-creative design processes can improve novelty, refinement, quality, and idea generation, while research on generative creativity also warns that gains in individual output quality may coincide with reduced collective diversity.

This study develops a team-centered framework for artificial intelligence–mediated creativity in collaborative design. Four hypothetical collaboration conditions were modeled: human-only collaboration, AI-first production, human-led AI divergence, and structured team–AI co-creation. A synthetic sample of 96 design teams, comprising 24 teams per condition, was generated. Evaluation considered expert-rated creative quality, idea diversity, iteration efficiency, perceived team agency, and creative-fixation risk. The simulated results show that AI-first production improved speed but produced comparatively weak idea diversity and team agency. Human-led AI divergence achieved stronger creativity while maintaining meaningful designer participation. The structured team–AI co-creation condition generated the highest mean creative-quality score at 87.0, the strongest idea-diversity score at 85.4, and the highest team-agency score at 89.1. A box-plot analysis further showed a more consistently high creative-quality distribution under structured team–AI collaboration. These values are illustrative rather than empirical.

Keywords: artificial intelligence, collaborative design, human–AI co-creation, generative AI, team creativity, design ideation, creative collaboration, AI-mediated creativity, co-design, human-centered AI

1. Introduction

Collaborative design is fundamentally relational. Designers rarely generate complex products, services, interfaces, environments, or communication systems through isolated individual activity. Creative outcomes instead emerge through exchanges among people who possess different forms of expertise, experience, technical knowledge, cultural understanding, and aesthetic judgment. Team members frame problems, challenge assumptions, combine partial ideas, negotiate trade-offs, and repeatedly transform incomplete concepts into more coherent solutions. Generative artificial intelligence introduces a new participant into this process. Large language models, image-generation systems, multimodal models, and specialized design assistants can now propose concepts, synthesize references, generate variants, visualize alternatives, and respond interactively to design critique. Current design research therefore increasingly treats AI not merely as an automation tool but as a potential co-ideation or co-creation partner.

Empirical research indicates that structured human–AI collaboration can strengthen creative performance. Wang and colleagues developed a custom GPT-based Co-Ideator that used probing questions to help designers explore design problems more deeply rather than merely supplying ready-made solutions. Their evaluation found advantages in novelty and design quality compared with traditional ideation. A separate 2020 study involving 42 designers developed a Human–AI Co-Creative Design Process based on professional interviews and a controlled comparison with a traditional design process. The authors reported higher creative performance across the evaluated dimensions under human–AI collaboration and observed that novice and experienced designers benefited differently: novice designers gained particularly in idea generation, whereas experienced designers obtained greater value during refinement and quality development.

These benefits do not mean that increasing AI involvement automatically increases creativity. McGuire, De Cremer, and Van de Cruys found across two experiments that participants were less creative when they primarily edited AI-generated poetry than when they produced work themselves; the creativity deficit disappeared when the interface positioned the human as a genuine co-creator rather than a downstream editor. Their findings highlight creative self-efficacy and role structure as important components of successful human–AI collaboration. Similarly, research on collaboration design suggests that preserving meaningful human creative input can improve quality and user satisfaction, whereas stronger AI control can alter the diversity and character of outputs.

A further concern is collective homogenization. Doshi and Hauser showed that access to generative-AI ideas could improve assessments of individual creative outputs while reducing diversity across the population of outputs, demonstrating that higher average quality and broader collective originality are not necessarily the same outcome. This issue has direct implications for collaborative design teams. When several designers begin from suggestions produced by similar models, trained on overlapping cultural and visual patterns, teams may converge toward comparable concepts even while individual proposals appear polished. Research examining AI-generated cultural and architectural representations similarly raises concerns that generative systems can privilege relatively narrow representations of cultural context.

The resulting research problem is therefore not whether AI is capable of producing creative material. Contemporary models can generate highly novel-looking text, imagery, and concepts, and recent comparisons demonstrate strong performance on established divergent and convergent creativity tasks. The more consequential question for collaborative design is how teams should organize human–AI interaction so that computational generation expands rather than compresses collective creativity. The present study addresses this question through a simulation-based framework comparing four collaboration structures. It proposes that high-quality team–AI creativity requires human control of framing and evaluation, deliberate use of AI for divergent stimulation, independent human ideation before exposure to model outputs, transparent contribution tracking, and collective synthesis after AI-assisted exploration.

2. Objectives of the Study

2.1 To Evaluate How AI Collaboration Structure Influences Team Creativity

The first objective is to examine whether different ways of introducing generative AI into collaborative design produce different outcomes in creative quality, novelty, idea diversity, and iteration efficiency. Particular attention is given to the difference between AI-first production and human-led co-creation.

2.2 To Examine Team Agency, Participation, and Creative Fixation

The second objective is to investigate how AI-mediated workflows may influence designers' perceived creative agency and the risk that teams converge prematurely around highly polished machine-generated proposals. The study treats participation and psychological ownership as components of creative effectiveness rather than as secondary user-experience concerns.

2.3 To Develop a Structured Team–AI Co-Creation Framework

The final objective is to propose a collaboration architecture that allocates different responsibilities to humans and AI across problem framing, divergent ideation, exploration, critique, concept synthesis, refinement, and final evaluation.

3. Review of Literature

3.1 Human–AI Co-Creation in Contemporary Design Processes

Generative AI has shifted computational support in design from passive execution toward interactive participation. Earlier digital design tools primarily enabled designers to draw, calculate, model, render, or document ideas that originated elsewhere. Contemporary generative systems can themselves offer alternatives, ask questions, create visual stimuli, and generate variations in response to natural-language instructions. Recent systematic work describes human–AI co-creation as a developing field involving cognition, design process, methodology, and creative outcome rather than a single technical tool.

The Human–AI Co-Creative Design Process developed by Wang and colleagues provides particularly relevant empirical evidence. Their model organizes AI participation across concept definition, visual exploration, design development, and implementation integration. The experiment involved 42 designers and assessed creative support, novelty, refinement, quality, and number of ideas. Human–AI collaboration improved performance across the evaluated dimensions, but experience remained influential. Experienced designers used AI more selectively and retained stronger evaluation and synthesis capabilities, whereas novice designers benefited more substantially from the increased generation of alternatives.

The Co-Ideator framework developed in AI EDAM similarly illustrates the value of structuring AI as a provocative collaborator rather than a direct answer generator. The system asked designers sequential "how" and "why" questions intended to uncover implicit assumptions and encourage deeper exploration. The AI therefore participated through questioning, expansion, and critical stimulation. Recent research on AIdeation with professional designers also reports improvements in creativity, ideation efficiency, and satisfaction when human–AI interaction is deliberately designed around the ideation process rather than treated as unrestricted prompting.

These studies indicate that generative AI's creative value is partly determined by interaction architecture. A system capable of producing large numbers of concepts may perform differently when it generates complete solutions than when it challenges assumptions, presents analogies, supplies alternative perspectives, or helps externalize partially formed ideas.

3.2 Creative Agency, Self-Efficacy, and Team Collaboration

Creativity involves more than the technical quality of the final artifact. Creative workers also need to experience meaningful agency over the processes through which ideas are developed. McGuire and colleagues found that people who primarily edited AI-generated work were less creative than those who created independently, while co-creative interaction restored the deficit. Their study identifies creative self-efficacy as an important mechanism and concludes that humans should occupy a co-creator role rather than functioning merely as AI editors.

This finding becomes more complicated in teams because AI can affect relationships among human collaborators as well as relationships between a person and a machine. Collaborative creativity normally requires turn-taking, critique, mutual elaboration, negotiation, and shared attention. When a generative system produces a polished answer immediately, it can become an unusually powerful conversational anchor. Team members may spend their remaining time modifying the generated proposal rather than independently exploring alternatives.

Research specifically examining collaborative creative work has begun to identify these effects. A CHI 2020 study involving 52 participant pairs investigated how generative AI changed collaborative creativity and how users assessed AI's contribution to the process, highlighting socio-technical implications for the design of creative AI systems. Other team-focused research similarly examines how access to generative AI alters creative teamwork rather than evaluating only individual prompting performance.

Recent reviews of human–AI co-creativity reinforce the importance of user control. A 2025 systematic review of 62 co-creative systems identified dimensions including creative phase, task, system proactivity, user control, embodiment, and model type. The review found that high user control was commonly associated with stronger satisfaction, trust, and ownership and emphasized the need to support thought externalization and transparent system behavior. These findings support a team model in which AI participates within a deliberately governed creative process rather than continuously determining what the group sees next.

3.3 Creativity Expansion, Homogenization, and Design Fixation

Generative AI can expand individual ideation by making unfamiliar associations available rapidly. This can be especially valuable during divergent phases when teams need broad alternatives rather than finalized solutions. Current empirical work shows that AI-supported design can improve novelty and facilitate idea generation, and recent experimental design studies report particularly strong benefits for less experienced designers who otherwise struggle to generate a wide range of alternatives.

At the same time, widespread reliance on generative systems can create a homogenization problem. Doshi and Hauser's experiment demonstrated that AI assistance increased the creativity and quality of individual stories while making the population of stories more similar to one another. This phenomenon is highly relevant to team design because a model's first suggestions can act as cognitive anchors. If all team members are exposed to the same generated alternatives before producing independent concepts, individual exploration may become constrained around a shared machine-generated reference point.

Research on visual and cultural representation further suggests that generative systems can reproduce limited patterns in the underlying information environment. Campo-Ruiz and colleagues found that AI-generated architectural imagery could narrow representations of cultural context in ways that risk reinforcing dominant conceptions of what counts as cultural representation. The issue is not simply bias in an ethical sense; it is also a creativity concern because teams seeking novel, locally meaningful, or culturally situated solutions may receive statistically common rather than contextually distinctive stimuli.

4. Research Methodology

4.1 Research Design and Synthetic Team Sample

The study adopts a simulation-based comparative design. A synthetic sample of 96 collaborative design teams was created, with 24 teams allocated to each of four collaboration conditions. Each hypothetical team contained four designers with complementary roles in research, visual design, interaction or product design, and concept evaluation.

Table 1: Experimental Conditions for AI-Mediated Collaborative Design

Collaboration Condition	Simulated Teams	Creative Workflow	Role of AI
Human-only collaboration	24	Independent ideation followed by team discussion, concept clustering, critique, and refinement	No generative AI
AI-first production	24	AI generates initial concepts before substantive team ideation; team edits and selects outputs	Primary early-stage generator
Human-led AI divergence	24	Team members ideate independently first, then use AI to expand, challenge, and recombine concepts	Divergent ideation partner
Structured team–AI co-creation	24	Human problem framing, independent ideation, AI divergence, team critique, AI-supported prototyping, human synthesis and final evaluation	Phase-specific co-creator

Source: Author's synthetic research framework. No actual teams are represented.

4.2 Measures of Collaborative Creativity

Five outcome dimensions were modeled.

Creative quality represented expert evaluation of novelty, usefulness, coherence, contextual relevance, and design development on a 0–100 scale.Idea diversity represented conceptual distance among the alternatives generated by a team, including variation in user proposition, interaction mechanism, service model, form, and implementation strategy.Iteration efficiency represented the extent to which a team developed multiple meaningful concept revisions within the available design period. Higher values indicate more productive iteration rather than simply faster output.

Team agency measured the extent to which designers could reasonably describe the final concept as the product of team judgment and meaningful creative participation.Creative-fixation risk represented premature convergence around an initial concept or aestheticdirection. Lower values indicate better preservation of divergent exploration.The model intentionally evaluates both output and process. This reflects current evidence showing that human–AI creative collaboration can increase task performance while still affecting motivation, perceived control, or psychological experience.

4.3 Simulation and Analytical Procedure

Twenty-four synthetic team observations were generated for each collaboration condition. Creative-quality distributions incorporated team-level variation rather than assigning identical outcomes to all teams. The box plot therefore represents the full simulated team distribution rather than only condition means.The collaboration conditions were designed around findings in the existing literature. AI-first production was modeled as faster than human-only work but more vulnerable to fixation and reduced ownership. The two human-led AI conditions were designed to represent workflows in which human problem framing and independent ideation occur before substantial AI generation. This design is consistent with research suggesting that human creative input and co-creator status influence both creativity and satisfaction.

The analysis is descriptive. No inferential significance testing is reported because the dataset was intentionally simulated. Future empirical research should preregister conditions, recruit actual multidisciplinary design teams, use blinded expert assessment, report inter-rater reliability, and separately analyze individual and team-level outcomes.

5. Analysis

5.1 Comparative Creative Performance

The synthetic results show that generative AI produced different effects depending on how it was introduced into the team process.Human-only collaboration achieved a mean creative-quality score of 70.8 and the second-highest team-agency score at 88.2. Idea diversity was also comparatively strong at 76.5, although iteration efficiency was lower than in AI-supported conditions.

AI-first production increased iteration efficiency to 86.2 because teams began with immediately available concepts and prototypes. However, its mean creative quality increased only moderately to 73.6, while idea diversity declined to 59.8 and fixation risk rose to 43.7.

Human-led AI divergence produced substantially stronger results. Creative quality increased to 83.2, idea diversity to 82.1, and iteration efficiency to 88.5, while fixation risk decreased to 23.6.The structured team–AI co-creation condition produced the strongest overall profile, including a mean creative-quality score of 87.0, idea diversity of 85.4, iteration efficiency of 92.1, and team agency of 89.1.

Table 2: Simulated Creative Outcomes Across Team–AI Collaboration Conditions

Collaboration Condition	Creative Quality	Idea Diversity	Iteration Efficiency	Team Agency	Creative-Fixation Risk
Human-only collaboration	70.8	76.5	68.4	88.2	27.9
AI-first production	73.6	59.8	86.2	62.5	43.7
Human-led AI divergence	83.2	82.1	88.5	81.4	23.6
Structured team–AI co-creation	87.0	85.4	92.1	89.1	19.8

Note: All values are synthetic scores on 0–100 scales. Lower creative-fixation scores are preferable
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5.2 Efficiency Does Not Automatically Produce Creative Diversity

The AI-first condition demonstrates the most important trade-off in the simulation. It produced substantially higher iteration efficiency than human-only collaboration but simultaneously generated the lowest idea-diversity score and highest fixation-risk score.

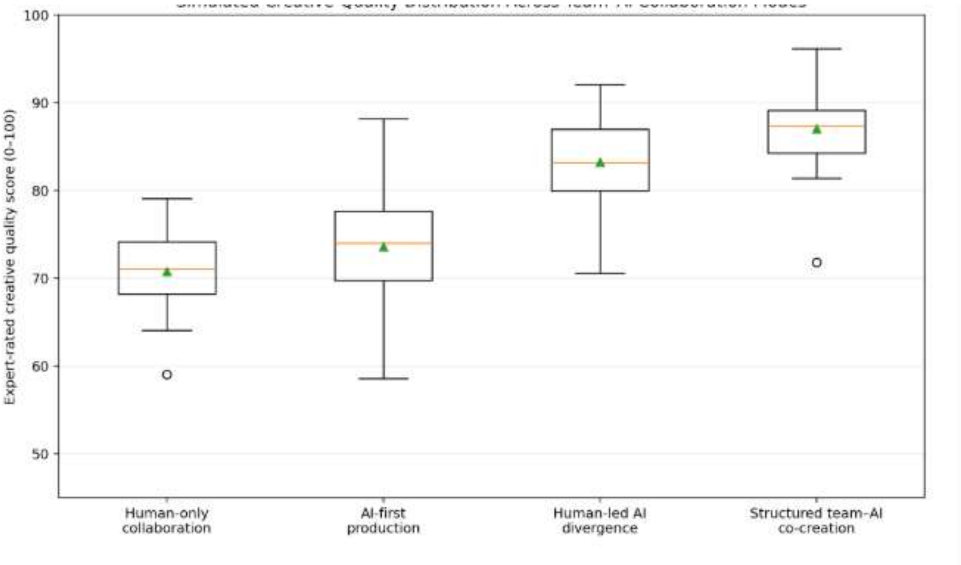
This pattern reflects existing empirical concerns. Generative AI can improve the evaluation of individual creative outputs while simultaneously increasing similarity across outputs. A design team that measures success primarily through concept-production speed may therefore misinterpret faster generation as broader exploration.

The human-led AI conditions avoid this problem by establishing an initial period of independent human divergence. Team members first externalize their own problem interpretations before being exposed to AI suggestions. The machine is then used to challenge, extend, recombine, or visualize human-originated directions.

The resulting process provides two sources of diversity: differences among human collaborators and generative variation supplied by AI. Final synthesis remains a collective human activity rather than a model-selection task.

5.3 Distribution of Creative Quality Across Teams

Graph 1: Simulated Creative-Quality Distribution Across Team–AI Collaboration Modes



The box plot shows clear differences not only in mean creative quality but also in the distribution of team performance. Human-only teams display a comparatively broad middle-range distribution. AI-first teams achieve a modest increase in central performance but do not show the same improvement as the more structured collaborative conditions.

The human-led AI-divergence condition shifts the distribution substantially upward, while the structured team–AI condition produces the highest median region and a comparatively concentrated high-quality distribution.

The graph is methodologically important because average scores alone can conceal variability among teams. A collaboration method that produces occasional exceptional outcomes but many weak outcomes may be less operationally useful than one that produces consistently strong results.

6. Discussion

6.1 Generative AI Should Expand the Team's Creative Search Space Without Defining It

The simulated results suggest that artificial intelligence contributes most effectively to collaborative design when it operates as a mechanism of creative expansion rather than as the origin of the team's problem definition. This interpretation is consistent with current human–AI co-design research showing that AI can stimulate idea generation, broaden conceptual exploration, and assist refinement while designers retain responsibility for framing and evaluative judgment. In the Human–AI Co-Creative Design Process studied by Wang and colleagues, AI performed different roles at different stages, while experienced designers continued to select, synthesize, and refine outputs through their own aesthetic and professional judgment. The Co-Ideator model reaches a similar conclusion from a different interaction strategy by having the AI ask provocative questions rather than immediately supplying finalized answers.

This distinction between expansion and definition is especially important in teams because the first externally supplied concept can reorganize the subsequent discussion. A polished AI-generated image or service concept may create a powerful reference point around which the group begins negotiating details. That process can feel highly productive because discussion becomes concrete quickly, but rapid concreteness may reduce exploration of alternative problem formulations. The simulated AI-first condition captures this risk through its high iteration-efficiency score and simultaneously elevated fixation score. The problem is therefore not that AI produces low-quality ideas. Contemporary models can perform strongly on conventional creativity tasks. The problem is that high-quality early outputs may become excessively persuasive before the team has constructed an independent understanding of the design problem.

A stronger workflow deliberately preserves a period in which human collaborators interpret the brief separately or in small groups before reviewing AI-generated material. This creates multiple cognitive starting points. AI can then be asked to challenge the existing alternatives, identify contradictions, generate counterexamples, introduce analogies, visualize radically different implementation approaches, or expose assumptions shared by all team members. The machine therefore increases search breadth without determining the initial boundaries of the search. Such sequencing is likely to be particularly useful in multidisciplinary teams because different professional perspectives are preserved before algorithmic suggestions begin to exert convergence pressure.

6.2 Collaborative Creativity Requires Human Agency, Not Merely Human Approval

The difference between AI-first production and structured team–AI co-creation also emphasizes the importance of creative agency. A workflow may technically retain a human in the loop while reducing the human role to selecting among machine-generated alternatives. Such a process preserves formal decision authority but may not preserve genuine authorship, psychological ownership, or creative self-efficacy. McGuire and colleagues showed that participants performed less creatively when placed primarily in the role of editing AI output and that positioning them as genuine co-creators changed the outcome. Broader research on human–AI collaboration similarly indicates that performance improvements can coexist with psychological costs such as reduced intrinsic motivation or perceived control.

Within collaborative teams, agency also has an interpersonal dimension. Design creativity depends on members believing that their observations and expertise can materially change the outcome. If AI becomes the dominant source of reference material, quieter team members may become even less likely to challenge an apparently authoritative generated proposal. Conversely, a structured process can use AI to increase participation. A model can help externalize rough ideas from members who are less comfortable sketching, generate alternative visualizations of verbally expressed concepts, or rapidly prototype several interpretations of competing team proposals. The critical difference is whether these functions increase the expressive capacity of team members or substitute for their participation.

The highest simulated team-agency score therefore occurs in the structured condition rather than in the human-only condition. This does not imply that AI necessarily increases agency in reality. Instead, it illustrates a specific design proposition: carefully orchestrated AI can lower technical barriers to expression while leaving judgment distributed among team members. Current co-creative design research similarly reports that less experienced designers may gain disproportionate assistance in early idea generation, whereas experienced designers contribute strongly through evaluation and refinement. A well-designed team process can exploit this complementarity by allowing AI to support expression without flattening differences in expertise.

6.3 Organizations Should Optimize for Collective Creativity Rather Than Maximum AI Utilization

The final implication is managerial. Organizations adopting generative AI in design teams may be tempted to evaluate the technology through conventional productivity indicators such as concepts generated per hour, time to first prototype, or number of visual alternatives. These measures capture useful efficiency gains but can reward workflows that generate many similar concepts or encourage premature convergence. Doshi and Hauser's findings demonstrate precisely why individual-level quality and population-level diversity need to be evaluated separately. Design organizations should therefore measure whether AI-supported teams explore genuinely different solution families, preserve contextual distinctiveness, and retain meaningful human participation rather than merely counting generated artifacts.

This approach also has implications for the design of AI interfaces. A productive co-creative system should make it easy to request contrast, contradiction, analogy, and alternative framing rather than simply improving prompt-to-output fidelity. It should allow teams to record which ideas originated independently, which emerged through AI interaction, and how concepts changed during synthesis. High user control and transparency are recurring considerations in the human–AI co-creativity literature, while recent systematic work also identifies gaps in support for early problem clarification and user adaptation. These observations support design environments in which AI participation can be delayed, intensified, or reduced according to the phase of the creative process.

The present study remains simulation-based and therefore cannot establish that the reported numerical differences will occur in real professional teams. Real outcomes will depend on team expertise, organizational culture, task ambiguity, model capability, prompting skill, client constraints, and the design discipline involved. Current empirical work is also frequently based on individuals, students, or relatively small samples, and researchers themselves call for broader design contexts and more complex collaborative settings. Future research should therefore conduct longitudinal studies with real multidisciplinary teams, measure creative diversity across projects rather than only within a single session, compare different AI interaction structures, and examine whether repeated AI use changes team ideation habits over time. Such studies should also investigate whether AI-generated convergence becomes stronger as teams increasingly share the same foundation models and creative reference systems.

7. Conclusion

Artificial intelligence is becoming an active participant in collaborative design rather than a peripheral production technology. It can generate concepts, challenge assumptions, visualize possibilities, accelerate iteration, and help designers overcome technical or expressive barriers. Contemporary empirical studies demonstrate that structured human–AI design processes can enhance creative performance and that co-creative systems can support novelty and quality when humans retain meaningful roles in the creative process.

The present study nevertheless demonstrates conceptually that the structure of collaboration matters as much as access to generative capability. In the synthetic analysis, AI-first production increased iteration efficiency but generated the lowest idea diversity, lowest team agency, and highest creative-fixation risk. The structured team–AI co-creation condition produced the strongest overall creative profile because AI entered the process after human framing and independent ideation and remained subordinate to collective critique and final human synthesis.

These numerical findings are simulated and should not be interpreted as empirical evidence. Their purpose is to establish a testable model in which team–AI creativity is assessed through multiple dimensions rather than through speed or output quality alone. Future studies should examine creativity, diversity, agency, fixation, participation, and longitudinal learning simultaneously.

A particularly important implication concerns the distinction between individual creativity and collective creative diversity. Generative AI may improve individual outcomes while simultaneously making outputs more similar across users. Collaborative teams should therefore preserve independent human ideation and multidisciplinary difference before exposing all members to a shared AI-generated solution space.

The appropriate goal is not to minimize AI involvement, nor is it to maximize it. Effective collaborative design requires creative orchestration: humans determine why the problem matters and what constitutes a meaningful solution; AI expands possibilities, generates contrasts, and accelerates experimentation; the team interrogates those possibilities through expertise, values, context, and critique; and final synthesis remains an accountable human creative act.Under this model, artificial intelligence does not replace collaborative creativity. It becomes a carefully positioned participant within it.

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