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From Outcomes to Experience: Designing AI to Support Agency, Collaboration, and Calibrated Trust in Creative Work

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ABSTRACT

AI is rapidly becoming embedded in design practice, from individual ideation to team collaboration and collective decision-making, yet evaluation still privileges short-term output metrics. We argue that outcome-centered paradigms are inadequate for Human-Centered AI because they under-measure the experiential conditions that sustain design innovation over time, including agency, creative self-efficacy, ownership, and calibrated trust. Drawing on HCI and creativity psychology, we conceptualize design innovation as a dynamic, situated process shaped by autonomy and competence, and by interactional work of synthesis, trade-offs, and attribution. As LLMs fluently generate concepts, proposals, and summaries, designers may shift from originators to selectors; even when outputs appear strong, this shift can weaken perceived ownership and diminish creative self-efficacy. At the team level, AI mediation can redistribute conversational authority, obscure provenance, and compress divergence, intensifying convergence pressures and participation inequities. For small-societies, legitimacy becomes central: participants must understand and contest how inputs are represented in the evolving collective record. We propose a design approach that treats LLM-based and multi-agent systems as configurable socio-technical mediators, articulated through seven principles: role-differentiated mediation, legibility of influence, provenance, contestability, divergence before convergence, reflection scaffolds, and trust calibration. We conclude with an evaluation agenda that complements output metrics with longitudinal measures of agency, innovation self-efficacy, ownership, participation equity, and procedural legitimacy.

Keywords: Human-centered AI, Human–AI collaboration, Agency, Ownership, Creative self-efficacy, Trust calibration, Provenance, Creative experience

INTRODUCTION

AI is rapidly moving from a standalone content generator to a fluent participant in design practice, spanning individual ideation, team collaboration, and collective decision-making. LLM-based systems can propose concepts, generate alternatives, summarize discussions, and recommend next steps. This shift intensifies a methodological mismatch: the dominant evaluation logic in human–AI creativity and creativity support tools often treats creativity as a property of the produced artifact, commonly operationalized through novelty, quality, quantity, or efficiency (Frich et al., 2019). Such measures are useful but incomplete. They capture visible outputs while overlooking cumulative

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changes in how people understand who is acting, who is responsible, and whose contributions matter.

This paper advances a position: the core challenge of AI at the human level is not that generative systems fail to perform, but that they can perform too well in ways that quietly displace human judgment, reflection, and responsibility. When this displacement becomes habitual, it can erode creative self-efficacy (Tierney and Farmer, 2002) and weaken shared ownership (Pierce and Jussila, 2010). It can also produce miscalibrated trust and reliance on AI outputs (Parasuraman and Riley, 1997; Lee and See, 2004). Addressing these risks requires a shift from outcome-centered evaluation to experience-centered design and assessment.

This position paper offers a multi-level framing of creative experience across individuals, teams, and small-societies; proposes seven principles for accountable AI mediation; and outlines an evaluation agenda that complements output metrics with longitudinal measures of agency, ownership, participation equity, and procedural legitimacy.

CREATIVITY AS A LIVED AND SOCIAL PROCESS

Creativity has long been understood as socially situated, emerging through interaction, negotiation, and synthesis (Csikszentmihalyi and Sawyer, 1995; Paulus, 2000; Harvey, 2014). Creativity support tools have expanded from aids for individual ideation to collaborative infrastructures, spanning card-based ideation systems and platforms for large-scale semantic organization (Golembewski and Selby, 2010; Siangliulue et al., 2016; Peters et al., 2021; Tseng, 2020; Hsieh et al., 2023; Kuo et al., 2019; Wang and Tseng, 2025a). These tools shape not only what is produced, but also how creators explore alternatives, interpret uncertainty, coordinate attention, negotiate meaning, and learn over time.

Creativity psychology provides mechanisms for why these experiential conditions matter. Creative self-efficacy captures beliefs about one's capability to generate and develop creative ideas, and predicts engagement and persistence under uncertainty (Bandura, 1977; Tierney and Farmer, 2002). Self-determination theory further suggests that sustained motivation depends on experiences of autonomy and competence (Ryan and Deci, 2000; Deci and Ryan, 2013). In teams, safety influences whether members voice novel ideas, challenge emerging consensus, and take interpersonal risks (Edmondson, 1999). These constructs are not secondary outcomes. They help determine whether creative practice is sustained and whether contributors develop ownership of the work (Pierce et al., 2001).

External stimuli can both enable and constrain ideation. Classic work on design fixation shows that exposure to examples can narrow the search space when interpreted as solutions rather than inspiration (Jansson and Smith, 1991), and later syntheses show that fixation effects depend on timing, framing, and creator strategies (Sio et al., 2015; Gonçalves et al., 2016). Generative AI now functions as a powerful and persistent source of stimuli. Its fluency and apparent plausibility can intensify fixation, compress divergence, and accelerate early convergence, particularly when outputs are treated as authoritative rather than provisional (Wadinambiarachchi et al., 2024).

FROM OUTCOMES TO EXPERIENCE: A MULTI-LEVEL FRAMING

We define creative experience as the cumulative interactional conditions through which people develop ideas while sustaining agency, motivation, responsibility, and trust. It unfolds across individual practice, team collaboration, and collective decision-making. This multi-level orientation is consistent with HCI research in other domains showing that effective technological support depends on attending simultaneously to individual, interpersonal, and broader sociocultural conditions, rather than treating support as a matter of individual use alone (Yuan et al., 2023).

Individual Level: Agency and Creative Self-Efficacy

At the individual level, AI can lower barriers to entry and support early exploration, for example by enabling reference recombination or metaphorical ideation (Choi et al., 2024; Zhou et al., 2025). However, as outputs become more fluent, users may shift from authors to curators, with effort concentrated on selecting and lightly editing AI-generated content. This role shift can remain invisible in outcome metrics, yet it can reshape attribution and creative self-concept. When success is repeatedly attributed to the system rather than to one's own competence, creative self-efficacy may weaken over time (Tierney and Farmer, 2002). Research in human–AI co-creative systems further indicates that agency is not a binary property but a negotiated experience, shaped by interaction design choices that distribute initiative, control, and responsibility between user and system (Rafner et al., 2025; Rezwana and Maher, 2023).

Team Level: Shared Ownership, Coordination, and Temporal Inequality

Participation in collaborative and online systems is typically highly unequal, often following power-law contribution patterns in which a small minority produces most visible content and coordination work (Kraut and Resnick, 2012). Empirical analyses often summarize this as the "90-9-1" pattern, where most members observe, a smaller portion contributes occasionally, and a very small fraction contributes intensively (Gasparini et al., 2020). We extend this concern to AI-mediated teamwork by using *temporal inequality* to describe how LLM-based summarization, drafting, and recommendation can unevenly allocate attention over time, stabilizing some contributions while compressing or erasing others in the evolving group record. Such shifts matter because ownership is not only individual but can become a fragile team resource, shaped by how contributions persist and are attributed in shared artifacts (Pierce et al., 2001). Teams already face coordination and convergence challenges, including cognitive load and premature narrowing of options (Kolfschoten and Brazier, 2013; Seeber et al., 2017), and AI can amplify these forces by compressing exploratory phases. Temporal inequality is an under-examined mechanism: rapid synthesis may privilege members who can articulate quickly, while disadvantaging those who rely on slower reflection or iterative sensemaking. Over time, such dynamics can undermine psychological safety and narrow the diversity of contributions (Edmondson, 1999).

Small-Society Level: Procedural Legitimacy

When creative and decision-making processes scale to hundreds of participants, the central challenge becomes legitimacy rather than ideation. AI is often proposed as a response to information overload through aggregation and summarization. Yet when selection and compression logics are opaque, participants cannot assess or contest how their contributions are represented, which can erode perceived fairness and willingness to participate. Procedural justice research shows that people evaluate not only outcomes but also the procedures through which decisions are made (Lind and Tyler, 1988; Tyler and Huo, 2002). Work on deliberative democracy similarly emphasizes that legitimacy depends on the transparency and quality of deliberation (Fishkin, 2009; Steenbergen et al., 2003). Recent evidence suggests that AI can support deliberation by helping groups identify common ground, while also raising practical questions about oversight, accountability, and institutional fit in deployment (Tessler et al., 2024).

Designing for legitimacy in AI-mediated small-societies therefore requires three interface and governance guarantees: (1) representation fidelity, such that the system preserves a traceable mapping between original contributions and aggregated outputs, including how minority positions were summarized or set aside; (2) contestation pathways, so participants can challenge, correct, or fork AI-generated summaries and rationales through clear procedures for incorporating revisions into the shared record; and (3) accountability surfaces, whereby the system exposes who initiated changes, what the AI modified, and which settings or policies shaped aggregation, supported by audit logs and role-based approval where appropriate.

DESIGN PRINCIPLES FOR EXPERIENCE-CENTERED AI

To support creative experience across levels, we propose seven design principles for LLM-based systems, including multi-agent architectures, where roles and authority can be explicitly configured.

Design Principle 1: Role-Differentiated Mediation

Separate AI roles such as exploration, synthesis, critique, and facilitation, and make the active role explicit to reduce the tendency to treat AI output as a single authoritative voice (Rezwana and Maher, 2023).

Design Principle 2: Legibility of Influence

Interfaces should make the AI's influence visible, including what was selected, merged, rewritten, or discarded, so users can understand how representations were transformed (Kizilcec, 2016).

Design Principle 3: Contestability and Revision Rights

Users and groups should be able to challenge summaries, restore omitted ideas, and propose alternative clusterings or framings. Contestability treats disagreement and revision as normal parts of creative work, not exceptions.

Accountability-oriented perspectives argue that systems should support contestation and auditability as design goals, not only predictive accuracy (Kroll et al., 2017).

Design Principle 4: Provenance and Attribution

Preserve links between ideas, contributors, and transformations to sustain ownership and responsibility as work evolves. Provenance should travel with artifacts so that credit, accountability, and interpretation remain intelligible across iterations. Psychological ownership theory suggests that people invest effort when their contributions are recognized and connected to outcomes (Pierce et al., 2001; Pierce and Jussila, 2010).

Design Principle 5: Support Divergence Before Convergence

Provide deliberate slowdown mechanisms, such as staged workflows that protect divergent exploration from early synthesis, introducing aggregation only after sufficient option generation. In group creativity, alternating individual and group idea generation can improve performance, in part by protecting novelty before evaluation and selection pressures dominate (Korde and Paulus, 2017).

Design Principle 6: Trust Calibration

Design for appropriate reliance by making uncertainty, system limitations, and boundaries of responsibility visible at the point of use. Research on automation misuse and automation bias shows that over-reliance is more likely under cognitive load and uncertainty, so trust calibration should be treated as a design responsibility rather than as a stable user trait (Parasuraman and Riley, 1997; Dzindolet et al., 2002; Lee and See, 2004). Appropriate reliance is also better supported when AI systems use bounded information sources, fit familiar communication channels, and preserve clear paths to human assistance rather than presenting themselves as standalone substitutes (Tseng et al., 2023).

Design Principle 7: Reflection Scaffolds

Include prompts and representations that help users articulate goals, assumptions, and rationale, so AI output supports reflection rather than substitution. Reflection and self-awareness can be assessed with validated measures to examine whether systems strengthen reflective practice (Grant et al., 2002; Govern and Marsch, 2001; Tseng and Liao, 2025).

AN EVALUATION AGENDA FOR AI AT THE HUMAN LEVEL

Experience-centered design requires evaluation methods that can detect cumulative effects, not only immediate output quality. We propose three complementary directions (Table 1): (1) longitudinal trajectories of self-efficacy and agency, (2) collaboration quality and shared ownership at the team level, and (3) procedural legitimacy in collective decision-making.

Table 1: Experience-centered constructs and example operationalizations across levels.

Level	Primary Construct	What to Measure	Data Sources
Individual	• Agency • Creative Self-Efficacy	• Self-Efficacy Trajectory • Perceived Ownership • Autonomy/Competence • Trust and Reliance Calibration	• Validated Scales • Experience Sampling • Interaction Logs • Think-Aloud
Team	• Shared Ownership • Coordination Quality • Temporal Inequality	• Contribution Persistence • Idea Provenance Coverage • Convergence Quality • Turn-Taking Balance • Participation Equity Over Time	• Discourse Analysis • Contribution Analytics • Meeting Logs • Version Diffs
Small-society	• Procedural Legitimacy	• Perceived Fairness • Representation Fidelity • Contestability Usage • Auditability Comprehension	• Surveys • Governance Logs • Appeal/Fork Rates • Qualitative Legitimacy Interviews

Longitudinal Trajectories of Self-Efficacy and Agency

Assess how creative self-efficacy, agency, and intrinsic motivation change through repeated use by combining validated scales, experience sampling, and interaction traces over time. To capture agency as enacted practice rather than attitude alone, complement self-report with behavioral and qualitative evidence, such as interaction logs, think-aloud data, and systematic analysis of how users set goals, negotiate constraints, and revise decisions across sessions.

Collaboration Quality and Shared Ownership

Move beyond productivity counts by measuring convergence quality, participation equity, and ownership. Convergence is a cognitive and social process shaped by how groups screen, select, and integrate ideas, and it can be assessed through both outcomes and process indicators (Seeber et al., 2017; Onarheim and Christensen, 2012). Ownership can be assessed at individual and collective levels by examining whether contributors feel recognized and responsible for the evolving work product (Pierce et al., 2001). Participation inequities can be diagnosed through discourse and contribution analyses, alongside team climate constructs such as psychological safety, which shapes whether members challenge syntheses and surface disagreement during integration (Edmondson, 1999).

Procedural Legitimacy in Collective Decision-Making

For larger collectives, evaluate perceived fairness, transparency, and the ability to contest AI mediation. Procedural justice theory provides validated constructs for legitimacy judgments, including whether people perceive decision processes as neutral, respectful, and correctable (Lind and Tyler, 1988; Tyler and Huo, 2002). Deliberation quality can be assessed using discourse-based indices that capture justification, respect, and inclusiveness (Steenbergen et al., 2003). Fairness perceptions in algorithmic decisions can also be examined through HCI work on justice and explanation, focusing on how explanations support contestability and accountability rather than mere acceptance (Binns et al., 2018).

MULTI-AGENT LLM SYSTEMS AS GOVERNANCE INFRASTRUCTURE

LLM-based multi-agent systems have been applied to complex design challenges (Tseng and Chang, 2025; Wu et al., 2024). We argue that multi-agent architectures are not only an engineering choice but also a design opportunity for human-level governance. By allocating responsibilities across specialized agents and making their interactions explicit, systems can render AI influence more legible, reduce single-voice authority, and introduce checkpoints for contestation and review.

A minimal configuration includes: (1) an Explorer that generates diverse alternatives; (2) a Critic that tests assumptions and highlights risks; (3) a Synthesizer that produces multiple competing summaries rather than a single canonical account; (4) a Facilitator that supports turn-taking, question asking, and preservation of minority viewpoints; and (5) an Auditor that logs transformations and prompts users to review consequential changes. Such role differentiation aligns with interaction modeling for co-creative systems and accountability goals (Rezwana and Maher, 2023; Kroll et al., 2017). Role separation also functions as a trust-calibration mechanism because it prevents defaulting to a single authoritative response and keeps critique, uncertainty, and alternative framings available for human judgment (Lee and See, 2004).

DISCUSSION AND CONCLUSION

The central risk of generative AI in creative work is not only error, but the gradual reshaping of practice when fluent system responses become the default basis for action. Without careful design, users may defer judgment and responsibility to the system, leading to miscalibrated reliance and weakened accountability. In design and innovation work, this may yield short-term gains in speed while reducing exploration, confidence, and learning over time. In teams and small-societies, it may accelerate convergence while weakening legitimacy and willingness to participate.

Human-centered AI has emphasized meaningful human control, transparency, and appropriate reliance. This paper extends that agenda by treating creative experience as a primary design target. Output metrics remain useful, but they are insufficient for evaluating AI in creative work. Taken together, our prior work suggests that AI systems are most effective when designed as socio-technical mediators embedded in existing practices, with ongoing human oversight and clear paths to human support rather than autonomous substitution (Tseng et al., 2023; Tseng et al., 2025; Wang and Tseng, 2025b). We therefore argue for experience-centered design and evaluation that recognizes creativity as a lived, socially situated process. By designing AI as an accountable mediator and assessing longitudinal effects on agency, creative self-efficacy, ownership, participation equity, and procedural legitimacy, we can better align LLM-based systems with sustained human flourishing in design practice.

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