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CREATIVITY AND ARTIFICIAL INTELLIGENCE IN DESIGN

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Abstract. This article examines the evolving relationship between creativity and artificial intelligence in design by analysing how artificial intelligence tools influence creative work within designer-led processes across design domains. A semi-systematic literature review of 67 studies maps artificial intelligence contributions to idea generation, decision-making, and conceptual exploration across stages of the design process. Findings inform a functional taxonomy grouping tools by creative support roles, stimulus generation, optimisation, evaluation, and hybrid workflow support, prioritising situated use over technological typologies. Recurring challenges include dependence on automated outputs, interface-driven shifts in ideation strategies and reduced diversity of exploration. The taxonomy enables assessment of how artificial intelligence contributes to ideation and refinement, informing research, education, and professional practice concerned with exploratory breadth, diversity, and workflow efficiency.

Keywords: design process, ethical considerations in artificial intelligence, generative artificial intelligence, human–artificial intelligence collaboration, non-generative artificial intelligence.

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1. Introduction

Artificial intelligence has moved from peripheral optimisation to a routine component of design work, influencing how ideas are generated, explored, selected, and refined within designer-led processes across domains such as product design, user experience design/ user interface, architecture, and visual communication (Fangwen Yu, 2025; Grilli & Pedota, 2024). This development has intensified debates about creativity as a property of individuals, systems, and socio-technical arrangements. Novelty and value remain baseline criteria, yet hybrid workflows increasingly condition the space of possibilities through algorithmic suggestions, learned regularities, and interface affordances (Runco, 2025). Tool ecosystems have diversified: generative systems support rapid variation from prompts (Sucupira Furtado et al., 2024), whereas non-generative systems support pattern recognition, recommendation, and decision support in tasks such as insight synthesis, clustering, and optimisation (Lechner, 2023). Scholarship often oscillates between technical categorisations and abstract debates about authorship, leaving limited task-level accounts of when artificial intelligence interventions matter for creative work. This article addresses this gap by deriving a taxonomy of creative support functions mapped to the Double Diamond (design process model) (Design Council, 2026). The objective is to characterise how artificial intelligence tools support, shape or constrain creativity during ideation, exploration and refinement, and to surface challenges relevant to responsible integration in practice and education.

2. Conceptual background

Creativity in design has been examined across psychology, cognitive science, and design theory and is commonly treated as both a cognitive process and a socially mediated activity. In design research, creativity is understood as a goal-directed, iterative sequence of problem framing, ideation, prototyping, and evaluation under ambiguity and shifting constraints (Dorst, 2019; Lawson, 2005). It unfolds through cycles of divergence and convergence shaped by experimentation and feedback. Componential accounts emphasise domain expertise, creative-thinking skills, and intrinsic motivation (Amabile, 1996), later extending creativity to dynamic environments that include technological agents (Amabile, 2020). Systems perspectives treat creativity as relational, negotiated between individuals, knowledge domains, and evaluative fields (Csikszentmihalyi, 1997), including clients, users, collaborators, and the data infrastructures and algorithms that mediate design work.

As design tools become more intelligent, authorship, and intention become increasingly difficult to disentangle. Collective creativity frames output as hybrid human–machine interaction in which computational systems participate in designer-led processes and interfaces accelerate iteration while steering exploration (Shneiderman, 2007). Empirical work similarly describes artificial intelligence as co-regulating pace and focus in early ideation (Haefner et al., 2021). In computational design, creativity can be analysed as an adaptive system in which designers engage with tools within a co-evolving cognitive ecology (Gero, 2020), sustained by iterative cycles of prompting, response, and evaluation. Such interactivity raises questions concerning agency, authorship, and epistemic legitimacy. As artificial intelligence systems are integrated into operational and cognitive functions, from option evaluation and data synthesis to proposal of variations, design authority may shift across actors and artefacts. Redistribution can reduce cognitive load and expand access to complex design spaces, yet it may also weaken critical reflection, obscure biases, and narrow conceptual diversity. Recent proposals extend creativity criteria beyond novelty and value to include authenticity and intentionality in hybrid human–artificial intelligence contexts (Runco, 2025). Authenticity concerns expression of a situated perspective; intentionality concerns goal formation, problem reframing, and self-directed exploration. Artificial intelligence-generated content can simulate novelty, while intentional agency and contextual rootedness remain contested, particularly where meaning is co-constructed with users, stakeholders, and environments. At organisational level, institutional conditions shape whether artificial intelligence supports exploration or prioritises efficiency (Grilli & Pedota, 2024). Artificial intelligence is treated as a socio-technical component within evolving creative systems, shaping problem framing, option prioritisation, and attention structures. Accordingly, the analysis foregrounds artificial intelligence intervention in real workflows, examining what is produced, structured, and appraised, rather than technical taxonomies, shifting attention from whether artificial intelligence is "creative" to when and how such intervention occurs. This framing grounds the taxonomy in subsequent sections, where artificial intelligence roles are mapped across Double Diamond phases (discover, define, develop, and deliver) based on interaction with creative work rather than internal mechanisms.

3. Methodological approach

This study adopts a semi-systematic literature review, combining interpretivist inquiry from information systems research (Oates, 2006) with procedural guidance from systematic review practices in design and management research (Snyder, 2019). The approach addresses two conditions: conceptual fragmentation across disciplines and rapid artificial intelligence innovation that outpaces conventional publication cycles. Following Snyder (2019), the review is treated as a theory-building method when guided by explicit inclusion logic and task-level analytical categories. The aim is not to assess technical performance, but to identify and classify the creative functions enacted within design practice. The review aligns with integrative and conceptual synthesis rather than exhaustive coverage.

Searches were conducted in October, 2024 in *Scopus*, *Web of Science*, *IEEE Xplore*, and *ScienceDirect*, selected for coverage of design research, human–computer interaction, cognitive systems, and computational creativity. Boolean conjunctive queries combined artificial intelligence, design, creativity, generative and non-generative (with syntax variations), prioritising studies addressing explicitly creative tasks (ideation, exploration, framing, prototyping, evaluation) rather than back-end optimisation or generic classification. Of 3229 records retrieved, title/abstract screening excluded 2596 for lacking design focus, treating artificial intelligence only in technical terms, or using creativity metaphorically; 633 full texts were assessed. Inclusion required: 1) explicit engagement with creativity as a design activity; 2) artificial intelligence use in at least one design-process phase; and 3) evidence of interaction between designers and artificial intelligence tools. The final corpus comprised 67 documents (48 peer-reviewed studies, 19 grey literature sources). Grey literature was included to capture practice-led developments in a fast-moving domain (Paez, 2017) and was retained only when it documented workflow integration, professional use, or ethical/epistemological reflection.

Each document was coded using a schema aligned with the taxonomic objective, informed by prior design-review practices (Wrigley et al., 2020). Coding dimensions included: artificial intelligence tool/system name; artificial intelligence type (generative, non-generative, or hybrid); creative function; design phase (Double Diamond); design domain; use context; evidence/document type; ethical reflection; and reported challenges. This enabled comparative synthesis of artificial intelligence roles across tasks and phases, with attention to creative support and human–artificial intelligence collaboration. Temporal and selection limitations warrant acknowledgement. The search closed in October, 2024; subsequent developments may not be represented. As interpretivist reviews are situated in time, findings should be read as snapshots rather than universal accounts (Oates, 2006). English-only inclusion and database indexing may also limit coverage. Nevertheless, the corpus provides a basis for the functional taxonomy developed in the following section.

4. Functional taxonomy of artificial intelligence in design creativity

Analysing how artificial intelligence reshapes creativity in design calls for a shift from technology-centred categorisations to function-oriented analysis. This section proposes a taxonomy based on the roles enacted across creative activity, drawing on 67 studies to relate artificial intelligence use to practical and ethical implications in design workflows. Creativity is treated as iterative and socially mediated and is defined here as the production of ideas or artefacts that are both novel and valuable (Runco & Jaeger, 2012). Boden's (2004) typology (combinational, exploratory, transformational) provides a lens for interpreting how many artificial intelligence systems primarily support combinational and exploratory variation, with transformational change typically requiring human curation.

Generative artificial intelligence refers to systems that produce new content from learned distributions, whereas non-generative artificial intelligence supports creativity through structuring, evaluation, and decision support. The taxonomy situates these roles across Double Diamond phases (discover, define, develop, and deliver) and treats artificial intelligence use as iterative and cross-phase rather than linear (Design Council, 2026; Fangwen Yu, 2025). Four recurrent functions are identified: 1) stimulating ideation, 2) structuring complexity, 3) guiding evaluation, and 4) refining outputs. Functions can co-occur and tools may occupy multiple categories depending on context and interaction mode; the taxonomy is therefore relational rather than hierarchical. The following mapping operationalises the taxonomy by locating dominant functions and tool types within each design phase, then synthesising patterns, trade-offs, and epistemological implications of artificial intelligence-mediated creativity.

4.1. Functional mapping of artificial intelligence tools across design phases

The analysis examines how artificial intelligence tools, classified as generative or non-generative, support specific phases of the design process. Grounded in the Double Diamond model (Design Council, 2026), creative functions are situated by phase, including points of divergence, convergence, and hybridisation between artificial intelligence types.

4.1.1. Discover: research, empathy, and contextual insight

The discover phase concerns problem-space understanding, including user needs, market dynamics and behavioural patterns. Non-generative artificial intelligence predominates, using clustering, recommendation, and pattern detection to synthesise user data and surface insights. Generative artificial intelligence appears less frequently, mainly for speculative scenarios and future-state visualisations that support reframing and team deliberation rather than direct decision-making.

4.1.2. Define: framing the problem and synthesising requirements

In define, non-generative artificial intelligence supports requirement structuring through predictive analytics, semantic clustering, and knowledge-graph representations to surface conflicts among stakeholder priorities (Lechner, 2023). Generative artificial intelligence is reported less often and is typically used for compressing early findings into draft briefs or visual/textual boundary objects for co-design communication (Ivcevic & Grandinetti, 2024).

4.1.3. Develop: ideation, conceptualisation, and prototyping

Develop concentrates generative artificial intelligence use; the literature review attributes 58% of reported generative instances to this phase. Systems such as *DALL-E*, *Stable Diffusion*, *ChatGPT*, and *DreamBooth* support rapid variation, aesthetic exploration, and early prototyping by externalising concepts and producing prompt-conditioned alternatives

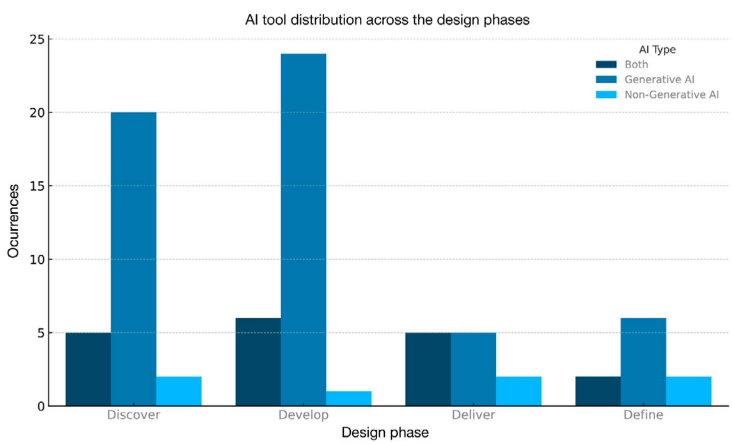
(Chandrasekera et al., 2024; Sucupira Furtado et al., 2024). This pattern aligns with exploratory creativity in which variation occurs within a constrained conceptual space (Boden, 2004). Reported trade-offs include fixation effects and homogenising learned regularities, where generated outputs narrow exploration or embed aesthetic bias, requiring sustained critique and contextual adjustment (Adeleye, 2024; Lee & Redstöm, 2025; Moruzzi, 2025). Non-generative artificial intelligence appears less frequently yet contributes to appraisal tasks (semantic coherence checks, concept screening, and analytic evaluation against design criteria), particularly in branding and communication contexts.

4.1.4. Deliver: testing, validation, and implementation

In deliver, non-generative artificial intelligence enables testing and optimisation through interaction simulation, accessibility checks, and predictive assessment of performance or efficiency (Haefner et al., 2021). Generative artificial intelligence is applied more selectively, mainly for localisation, content adaptation, and personalisation, as well as code generation and parametric scripting when integrated with domain tooling and quality assurance (Sucupira Furtado et al., 2024).

4.2. Cross-phase applications and hybridisation

Tool use frequently spans phases, challenging linear sequencing in the Double Diamond and reflecting recursive overlaps between exploration, evaluation, and refinement (Design Council, 2026; Wrigley et al., 2020; Doshi & Hauser, 2024; Gero, 2020). Figure 1 summarises this distribution: generative systems cluster in develop, non-generative systems concentrate in discover/define, and hybrid configurations appear across all phases by coupling generation with analytic filtering and contextual checks (Fangwen Yu, 2025; Chandrasekera et al., 2024;



Note: AI – artificial intelligence.

Figure 1. Frequency of artificial intelligence tool applications reported in the literature, organised by design phase according to the Double Diamond (design process model) (source: created by author)

Sucupira Furtado et al., 2024; Lechner, 2023; Flechtner & Stankowski, 2023). Hybrid platforms incorporate interactive feedback loops that enable iterative critique and parameter adjustment, blurring conventional boundaries between conceptualisation and assessment (Haefner et al., 2021; Fangwen Yu, 2025).

4.3. Aligning artificial intelligence tools with the cognitive stages of the creative process

Beyond the procedural logic of the Double Diamond, creativity unfolds through cognitive phases characterised by distinct mental operations and epistemic demands. Wallas' (1926) four-stage model, 1) preparation, 2) incubation, 3) illumination, and 4) verification, describes transitions from immersion to insight and subsequent appraisal. Integrating this model into the taxonomy shifts attention from design activities to the cognitive processes that precede and shape them. Table 1 pairs each stage with representative tool families and corresponding creative functions.

This alignment provides an interpretive bridge to the critical synthesis, where phase distributions and functions are discussed in relation to agency, bias and evaluative criteria. In preparation, artificial intelligence can assist with cognitive offloading by structuring complexity, synthesising information, and supporting sensemaking. In incubation, generative tools may prompt unexpected associations and alternative framings that support lateral exploration. In illumination, rapid variation can help externalise tentative ideas for appraisal and iteration. In verification, analytic and simulation-oriented tools can support refinement against functional, contextual, and aesthetic criteria. These stages are not strictly sequential and may overlap or recur; similarly, tools may be used across multiple cognitive registers within a single workflow.

Table 1. Alignment of artificial intelligence tools with the cognitive stages of the creative process (source: created by author)

Creative stage (Wallas, 1926)	Representative artificial intelligence tool	Creative function	Artificial intelligence type	Functional contribution
Preparation	*ChatGPT*, *Adobe Sensei*	Structuring complexity	Non-generative, hybrid	Supports data synthesis, trend analysis, and requirement specification
Incubation	*Midjourney*, *RunwayML*	Stimulating ideation	Generative, hybrid	Produces variations that foster associative exploration and visual provocation
Illumination	*DALL-E*, *Adobe Firefly*	Guiding evaluation and ideation	Generative	Externalises alternatives for rapid appraisal, supporting insight formation through iteration
Verification	*Revit Dynamo*, *Autodesk Forma*	Refining outputs and structuring	Non-generative, hybrid	Assists in simulation, refinement, validation, and production documentation

For design education, the model shifts emphasis from software training to epistemic literacy: recognising which tools support divergent *versus* convergent thinking, associative exploration *versus* evaluative appraisal, and how artificial intelligence can augment reasoning as well as output. The analytic task is therefore to characterise how creative work is reconfigured through collaborative human–artificial intelligence interaction rather than as a contrast between human creativity and automation.

4.4. Critical synthesis: patterns, tensions, and theoretical implications

The taxonomy and phase mapping indicate recurring patterns in how artificial intelligence is taken up in design creativity, with implications for epistemology, agency, and professional practice. First, a functional asymmetry emerges: generative systems concentrate in ideation and conceptual visualisation, whereas non-generative systems support decision structuring, analytic insight, and later-stage assessment. This distribution aligns with divergent and convergent dynamics in design thinking (Brown, 2008; Lawson, 2005), while hybrid systems blur phase boundaries and enable "temporal elasticity" in collaboration, with iteration and feedback becoming less sequential (Haefner et al., 2021).

Second, reported use concentrates in representational domains (*e.g.*, graphic design, user experience design/user interface, speculative ideation), where rapid externalisation and stylistic variation are central. The literature also reports homogenising learned regularities: stylistic defaults and recurring tropes embedded in training data may constrain exploration and reproduce dominant design cultures, including Western-centric aesthetic codes (Grilli & Pedota, 2024; Moruzzi, 2025). By contrast, non-generative artificial intelligence remains less visible in public discourse despite shaping creative strategy through recommendation, clustering, segmentation, and prediction. Such systems frame what becomes thinkable and comparable, influencing selection and trade-off negotiation, and may remain unacknowledged because they rarely produce salient artefacts, while still shaping design reasoning (Gero, 2020; Ivcevic & Grandinetti, 2024). A third pattern concerns automation and authorship. Artificial intelligence-assisted acceleration unsettles conventional markers of originality and ownership, producing a spectrum of professional stances, from artificial intelligence-as-collaborator to artificial intelligence-as-sketching aid with restricted attribution. Creativity in artificial intelligence-supported design is increasingly described as relational, emerging through interaction, critique, and selection rather than residing in tools or individuals (Fangwen Yu, 2025; Chandrasekera et al., 2024). This accompanies shifts in how constraints and trajectories are interpreted and negotiated, raising questions of intentionality, responsibility, and transparency in design decisions (Cross, 2006).

Ethical implications emerge most clearly around authorship, traceability, and bias. Generative systems often depend on large and opaque datasets, amplifying concerns about cultural appropriation, bias replication, and the reproduction of historical inequities (Moruzzi, 2025). These concerns align with calls for explainable artificial intelligence and contestable systems that render algorithmic reasoning inspectable and accountable within design practice (Doshi & Hauser, 2024). The functional taxonomy therefore clarifies when artificial intelligence becomes epistemically relevant in creative work and supports discussion of the literacy, evaluative criteria, and pedagogical approaches implied by artificial intelligence-mediated workflows.

5. Artificial intelligence as a catalyst for practice and learning

From the functional taxonomy follow specific competencies and pedagogical priorities implied by artificial intelligence integration in design. In professional settings, artificial intelligence tools support visual composition, aesthetic judgement, and user-behaviour mapping under designer supervision, reinforcing hybrid workflows that couple design judgement with computational inference (Sucupira Furtado et al., 2024). Beyond tool fluency, professional practice requires judgment in machine-mediated environments: interpretive capacity to interrogate and refine artificial intelligence outputs in context (Doshi & Hauser, 2024). Empirical accounts also report artificial intelligence use for conceptual framing and constraint exploration, including early-stage brief development (Lee et al., 2025).

Design education requires extension beyond traditional studio pedagogy. As emphasized by some authors (Wang et al., 2025; Griebel et al., 2020), the goal is not to replace human creativity but to enhance it. AI should support the designer's intent, amplify personal expression, and respond to cultural context, not override or obscure them. Core curricular priorities include artificial intelligence literacy (training logics, data provenance, and failure modes), human–artificial intelligence collaboration competence (critical interpretation and iterative inquiry), and ethical grounding (exclusions, normative aesthetics, and accountable use) (Moruzzi, 2025). A more-than-human orientation further positions artificial intelligence as an active participant in meaning-making rather than a neutral interface, requiring pedagogies attentive to relational co-agency, and plural epistemologies (Wakkary, 2021; Nicenboim et al., 2024; Giaccardi et al., 2025). Human-centred design remains a normative anchor: intent, expression, and cultural context should organise artificial intelligence-mediated work, with responsibility for interpretive framing and final curation retained within design practice.

6. Conclusions: reframing creativity in the age of artificial intelligence

This study examined how generative and non-generative artificial intelligence tools are integrated into contemporary design practice, supporting and at times constraining creativity across ideation, exploration and refinement. A systematically structured literature review informed a functional taxonomy of artificial intelligence roles across creative workflows. By prioritising creative functions over technical typologies, the taxonomy reflects situated uses and recurrent challenges. Generative artificial intelligence is most frequently used in early conceptual work, expanding visual and textual option spaces while also introducing fixation effects, aesthetic convergence, and contextual misalignment. Non-generative artificial intelligence is more prominent in convergent work, supporting information structuring, option appraisal and alignment with technical and user-centred criteria. Hybrid configurations increasingly combine generation with analytic filtering and iterative feedback, enabling recursive collaboration across phases, and foregrounding how creative agency is negotiated in human-artificial intelligence workflows.

The contribution comprises three elements: 1) a functional taxonomy situating artificial intelligence roles across Double Diamond phases; 2) a synthesis of empirical patterns and trade-offs, including epistemic and ethical implications; and 3) implications for education and professional development centred on literacy, collaboration capability, and conditions that sustain human-centred creativity. Creativity in artificial intelligence-augmented design is conceptualised as relational and situated within socio-technical systems, shaped by contextual feedback, and contingent on designerly judgement and critical interpretation. Future research may extend this functional lens through domain-specific studies of appropriation, team collaboration patterns, and cross-cultural mediation of artificial intelligence-generated outputs. The taxonomy offers conceptual guidance for integrating artificial intelligence in ways that sustain depth, diversity, and integrity in creative work.

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