



The Co-Creative Human-AI Nexus: A Phenomenological and Experimental Study on How Generative Tools Reshape Divergent Thinking in Industrial Design

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Article Info

Received: January 12, 2026

Revised: March 15, 2026

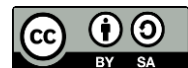
Accepted: April 10, 2026

Online Version: June 23, 2026

Abstract

Generative artificial intelligence is increasingly embedded in industrial design, yet its effects on divergent thinking remain contested because rapid idea production may coexist with fixation, reduced agency, and uncertain authorship. This study examined how generative tools reshape fluency, flexibility, originality, and elaboration during early design ideation while exploring designers' lived experiences of human-AI co-creation. A mixed-methods design combined a randomized pretest-posttest experiment with phenomenological interviews. One hundred twenty industrial design students were assigned to AI-assisted or conventional ideation conditions, while twenty participants were purposively selected for in-depth interviews. Divergent-thinking performance, process logs, questionnaires, sketches, prompts, and interview transcripts were analyzed using ANCOVA, correlation analysis, and thematic interpretation. The AI-assisted group achieved significantly higher posttest scores across all divergent-thinking dimensions, with the strongest effects in fluency and flexibility. Conceptual reframing and prompt revision were positively associated with originality, whereas direct adoption of generated outputs was linked to fixation, lower autonomy, and authorship uncertainty.

Keywords: Co-Creation, Divergent Thinking, Generative Artificial Intelligence



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Journal Homepage

<https://research.adra.ac.id/index.php/innovatsioon>

How to cite:

Fawaz, O., Moukadem, R., & Kassem, J. (2026). The Co-Creative Human-AI Nexus: A Phenomenological and Experimental Study on How Generative Tools Reshape Divergent Thinking in Industrial Design. *Journal of Loomingulus ja Innovatsioon*, 3(3), 1–15. <https://doi.org/10.70177/innovatsioon.v3i3.4341>

Published by:

Yayasan Adra Karima Hubbi

INTRODUCTION

Generative artificial intelligence has rapidly entered creative industries and transformed the ways designers explore, visualize, and communicate ideas (Dong et al., 2026; Khan et al., 2026; Nakagomi et al., 2026). Text-to-image generators, generative modeling systems, conversational design assistants, and algorithmic ideation platforms can produce numerous visual alternatives within a relatively short period. Industrial design, which traditionally depends on iterative sketching, material exploration, user-centered reasoning, and physical prototyping, now operates within an expanding computational environment. This development has created new opportunities for designers to accelerate early-stage concept generation, examine unconventional forms, and access visual references beyond their immediate experience. The integration of generative tools into design practice therefore represents more than a technical improvement; it signals a fundamental change in the relationship between human imagination, computational production, and creative decision-making.

Divergent thinking occupies a central position in industrial design because it enables designers to generate multiple, varied, and potentially original responses to an open-ended problem. Fluency, flexibility, originality, and elaboration are commonly treated as important dimensions of divergent thinking during ideation (Joe Qin, 2026; Shen & Lin, 2026; Yamprai, 2026). Conventional design education encourages these capacities through brainstorming, sketching, analogy, morphological analysis, collaborative discussion, and repeated experimentation. Generative AI introduces a new source of stimulation into this process by offering unexpected visual combinations, stylistic variations, structural alternatives, and conceptual associations. The presence of such tools may expand the range of ideas available to designers, yet it may also influence how they define problems, evaluate possibilities, and determine which ideas deserve further development.

Human–AI interaction in creative work is increasingly understood as a co-creative relationship rather than a simple process of automated content production (Atkova et al., 2026; C. Wei, 2026; Yang et al., 2026). Designers provide prompts, constraints, references, contextual knowledge, aesthetic judgment, and evaluative feedback, while generative systems return visual or verbal outputs that may stimulate further exploration. Creative outcomes emerge through repeated cycles of prompting, interpreting, selecting, rejecting, and refining. This reciprocal process forms what may be described as a co-creative human–AI nexus, in which agency is distributed across human intention and machine-generated possibilities. A rigorous examination of this nexus is needed to determine whether generative tools genuinely strengthen divergent thinking or merely create an appearance of creativity through the rapid production of numerous variations.

The increasing use of generative AI in industrial design has developed faster than scholarly understanding of its cognitive and experiential consequences (Altinay et al., 2026; Lee & Wei, 2026). Existing discussions frequently emphasize efficiency, productivity, accessibility, and visual output quality, while paying less attention to changes in the designer's thinking process. Rapid idea generation may increase the number of alternatives produced during ideation, but numerical abundance does not necessarily indicate conceptual diversity or creative originality. Several generated concepts may differ visually while remaining structurally similar, aesthetically repetitive, or dependent on patterns embedded in the system's training data. The central problem concerns whether generative tools deepen divergent exploration or simply accelerate the reproduction of familiar design conventions.

Designer agency presents another important problem within AI-assisted ideation. Generative systems can introduce unexpected forms and associations, yet their outputs may also redirect attention toward ideas that are visually impressive but contextually weak (Al Fadhel et al., 2026; Du & Qiao, 2026; Prajapati et al., 2026). Designers may become anchored to the first convincing images generated by the system, especially when these images appear polished and professionally rendered. Such anchoring can reduce the motivation to explore

alternative problem definitions, functional principles, cultural meanings, manufacturing constraints, or user experiences. The dependence on algorithmically suggested possibilities raises concerns about authorship, intentionality, critical judgment, and the extent to which designers remain active creators rather than selectors of machine-produced options.

Methodological limitations complicate current attempts to assess the influence of generative AI on creativity. Studies that rely exclusively on output counts, creativity scores, or participant satisfaction may overlook the lived experience of uncertainty, surprise, frustration, control, dependency, and discovery during human–AI collaboration (Amoozad Mahdiraji et al., 2026; Baffour Gyau et al., 2026; X. Wei et al., 2026). Qualitative accounts alone may also be insufficient because positive perceptions of usefulness do not necessarily correspond to measurable improvements in divergent thinking. The research problem therefore requires an integrated design capable of examining both observable creative performance and subjective experience. A combination of phenomenological inquiry and experimental comparison offers a more comprehensive basis for understanding how generative tools reshape ideation in industrial design.

The primary objective of this study is to investigate how interaction with generative AI influences divergent thinking during the early stages of industrial design. The study seeks to determine whether AI-supported ideation affects the fluency, flexibility, originality, and elaboration of design concepts when compared with conventional human-led ideation (Asad et al., 2026; Coelsch-Foisner et al., 2026; Kannikar & Sangnak, 2026). Attention will be directed not only toward the quantity of ideas but also toward the conceptual distance among alternatives, the diversity of design categories explored, and the depth with which promising concepts are developed. This objective positions divergent thinking as a multidimensional creative capacity rather than a simple measure of production speed.

The phenomenological objective is to explore how industrial designers experience co-creation with generative tools. The inquiry will examine designers' perceptions of creative agency, ownership, inspiration, cognitive stimulation, uncertainty, dependence, and control throughout the ideation process (Akgün et al., 2026; Alzeiby et al., 2026; Ripollés & Blesa, 2026). Particular attention will be given to moments when AI outputs disrupt established assumptions, encourage new directions, produce confusion, or constrain exploration through visually dominant suggestions. The phenomenological component is expected to reveal how designers interpret the presence of a nonhuman creative partner and how those interpretations shape their engagement with design problems.

The experimental objective is to compare creative performance across distinct ideation conditions, such as unaided design, AI-assisted design, and potentially structured human–AI co-creation (Cerchione et al., 2026; Hao et al., 2026; Ke & Luo, 2026). The comparison will assess whether generative tools produce statistically and practically meaningful differences in divergent-thinking outcomes. Process-related variables, including time allocation, number of iterations, prompt modifications, concept selection patterns, and degree of reliance on generated outputs, may also be examined. The combined objectives are intended to establish relationships among tool use, creative behavior, subjective experience, and final concept quality, thereby producing a more complete account of AI-mediated industrial design.

Current research on generative AI and creativity is distributed across fields such as computational creativity, human–computer interaction, education, marketing, visual communication, and digital art (Fünfgeld et al., 2026; Lin, 2026; Qian et al., 2026). Industrial design remains comparatively underexamined despite its distinctive combination of aesthetic, functional, ergonomic, technological, and manufacturing considerations. Findings derived from general writing tasks or artistic image production cannot automatically be transferred to industrial design because product ideation involves constraints that extend beyond visual novelty. A disciplinary gap exists in understanding how generative systems influence divergent

thinking when designers must balance originality with usability, feasibility, sustainability, user needs, and production requirements.

A conceptual gap is visible in the tendency to equate generative abundance with creative enhancement. Many assessments treat the production of more outputs as evidence that AI increases creativity, even though generated alternatives may contain superficial rather than fundamental differences. Limited attention has been paid to whether AI-assisted designers explore a wider range of functional principles, user scenarios, material strategies, product architectures, and cultural interpretations. The distinction between visual variation and conceptual divergence remains insufficiently developed. This study addresses that gap by treating divergent thinking as a structured construct involving fluency, flexibility, originality, and elaboration rather than relying solely on the number or attractiveness of generated images.

A methodological gap also persists because experimental and phenomenological approaches are often applied separately. Controlled experiments can identify performance differences but may fail to explain why those differences occur or how participants experience them. Phenomenological studies can provide rich descriptions of human–AI interaction but may not demonstrate whether perceived benefits correspond to measurable creative outcomes. Mixed evidence is especially necessary in co-creative contexts, where effectiveness depends on both computational output and human interpretation. The integration of experimental measurement with phenomenological analysis allows the study to connect quantitative changes in divergent thinking with the meanings designers attribute to their interactions with generative systems.

The novelty of this research lies in its treatment of generative AI as an active element within a co-creative cognitive system rather than as a neutral instrument for producing design images. The study conceptualizes creativity as emerging from iterative exchanges among human intention, prompt formulation, algorithmic response, interpretation, evaluation, and refinement. This perspective challenges both technological determinism, which assumes that advanced tools automatically improve creativity, and human exceptionalism, which dismisses computational contributions as merely derivative. The proposed framework enables a more nuanced examination of distributed creative agency and clarifies how designers negotiate control within AI-supported ideation.

The integration of phenomenological and experimental evidence constitutes a second area of novelty. Measurable changes in divergent-thinking performance will be interpreted alongside designers' lived experiences of surprise, ownership, cognitive extension, fixation, dependency, and critical judgment. Such integration can reveal discrepancies between perceived and actual creative enhancement. Designers may feel more creative because AI produces polished outputs rapidly, while independent evaluation may identify limited conceptual variety. Other participants may initially feel less autonomous but ultimately generate more original solutions through productive disruption. Examining these possible tensions will produce findings that are theoretically richer and methodologically stronger than conclusions derived from a single research approach.

The study is justified by the urgent need for evidence-based guidance in industrial design education, professional practice, and responsible AI development. Design schools require pedagogical models that teach students to use generative tools without weakening foundational abilities in sketching, problem framing, critical evaluation, and independent ideation. Professional organizations require clearer knowledge of when AI supports exploration and when it creates fixation, homogenization, or excessive reliance on automated suggestions. Technology developers require insight into interface features that preserve human agency, encourage conceptual diversity, and make the origins and limitations of generated outputs more transparent. The expected contribution extends beyond determining whether generative AI is beneficial or harmful; it explains the conditions under which human–AI co-creation can enrich

divergent thinking while maintaining intentionality, accountability, and intellectual ownership in industrial design.

RESEARCH METHOD

Research Design

This study will employ a mixed-methods research design that integrates a controlled experiment with a phenomenological inquiry. The experimental component will examine the measurable influence of generative artificial intelligence tools on divergent thinking during the early stages of industrial design ideation. The phenomenological component will explore how participants experience, interpret, and negotiate creativity, agency, control, authorship, and cognitive stimulation while collaborating with generative systems. The integration of these two approaches is intended to provide a comprehensive understanding of both the observable effects and the subjective meanings of human–AI co-creation.

The experimental component will adopt a randomized pretest–posttest control-group design. Participants will be assigned to either an AI-assisted ideation group or a conventional ideation group (Barile & Secundo, 2026; Kolagani et al., 2026; Olan et al., 2026). Participants in the AI-assisted group will use a generative text-to-image or multimodal design platform during the concept-development process, while those in the conventional group will generate ideas through manual sketching, written brainstorming, and standard digital drawing tools without generative assistance. Both groups will complete equivalent industrial design tasks under the same time allocation, design brief, workspace conditions, and assessment criteria. The controlled arrangement will allow differences in divergent-thinking performance to be associated more carefully with the use of generative tools.

The phenomenological component will follow an interpretative phenomenological orientation to investigate participants' lived experiences during AI-supported ideation. Particular attention will be given to experiences of surprise, inspiration, uncertainty, fixation, dependence, ownership, creative confidence, and perceived loss or expansion of control. Participants' accounts will be examined as situated interpretations rather than treated as direct descriptions of technological effects. Quantitative and qualitative findings will be integrated during the interpretation stage to identify whether participants' perceptions of creative enhancement correspond with measurable changes in fluency, flexibility, originality, and elaboration.

Research Target/Subject

The target population will consist of undergraduate and postgraduate industrial design students who have completed foundational courses in design thinking, product sketching, concept development, and digital visualization (Conzatti et al., 2026; Dai et al., 2026; Kim et al., 2026). This population is considered appropriate because the participants possess sufficient design knowledge to understand an open-ended design brief while remaining actively engaged in the development of their creative practices. Students with extensive professional experience in generative design or commercial AI-assisted product development will be excluded to reduce substantial differences in prior expertise.

A sample of approximately 120 participants will be recruited from industrial design programs at selected universities. Participants will be selected using purposive eligibility screening followed by random assignment to the experimental conditions. The AI-assisted group will consist of approximately 60 participants, while the conventional ideation group will include approximately 60 participants. Sample adequacy will be reviewed through an a priori statistical power analysis based on the expected effect size, significance level, and required statistical power. Demographic and academic characteristics, including age, gender, level of

study, design experience, digital literacy, prior use of generative AI, and frequency of sketching practice, will be documented to evaluate group comparability.

A purposive subsample of approximately 20 participants will be selected for the phenomenological inquiry after the experimental sessions. Selection will seek maximum variation in creative performance, prior AI experience, interaction patterns, and perceived usefulness of the generative tool. Participants showing high, moderate, and low changes in divergent-thinking scores will be included to prevent the qualitative analysis from representing only positive or successful experiences. Recruitment will continue until the interview data demonstrate sufficient experiential depth and no substantially new thematic meanings emerge.

Research Procedure

The primary experimental instrument will be an open-ended industrial design task developed to elicit divergent thinking. Participants will be asked to generate multiple product concepts in response to a design brief addressing a realistic social, functional, or environmental problem. The brief will specify the intended users, design context, practical constraints, and expected outputs without prescribing a single solution. Equivalent task versions will be reviewed by industrial design experts to ensure comparable levels of complexity, relevance, and creative opportunity. A pilot test will be conducted to evaluate clarity, completion time, and potential differences in task difficulty.

Divergent-thinking performance will be assessed through an analytical scoring rubric covering fluency, flexibility, originality, and elaboration. Fluency will refer to the number of relevant concepts produced, while flexibility will represent the number of distinct conceptual categories or functional approaches. Originality will be evaluated according to the rarity, novelty, and conceptual distance of the proposed solutions. Elaboration will reflect the extent to which participants develop functional details, user interactions, materials, mechanisms, and contextual explanations. Three independent assessors with expertise in industrial design will evaluate anonymized outputs. Inter-rater reliability will be examined using an intraclass correlation coefficient to ensure consistency across assessors.

A creativity-support perception questionnaire will be administered after the ideation session. The questionnaire will measure perceived creative stimulation, efficiency, autonomy, cognitive effort, confidence, fixation, satisfaction, and reliance on the tool. Items will be rated using a five-point Likert scale ranging from strong disagreement to strong agreement. The instrument will be adapted from established measures of creativity support, human–computer interaction, and technology-assisted creative agency. Content validity will be assessed through expert judgment, while internal consistency will be evaluated using Cronbach’s alpha.

A semi-structured interview protocol will serve as the principal instrument for the phenomenological component. Interview questions will examine how participants initiated ideas, interpreted generated outputs, revised prompts, selected alternatives, rejected suggestions, and experienced changes in their creative direction. Questions will also address authorship, emotional response, cognitive dependency, perceived collaboration, ethical concerns, and the difference between generating an idea and choosing an algorithmically produced option. Reflective prompts will encourage participants to describe specific moments from the design session rather than provide only general opinions about artificial intelligence.

Process-recording instruments will include screen recordings, prompt histories, timestamps, concept-development sheets, sketch archives, and researcher observation notes. These records will document the number of prompts, frequency of revisions, duration of interactions, transition between concepts, and degree of direct adoption of generated outputs. Process data will support the interpretation of both performance scores and interview narratives. Participant identities will be replaced with coded identifiers, and all digital records will be stored in encrypted research folders.

Instruments, and Data Collection Techniques

Ethical approval will be obtained from the relevant institutional review board before participant recruitment and data collection. Prospective participants will receive written information explaining the research objectives, procedures, potential risks, confidentiality safeguards, voluntary participation, and right to withdraw. Written informed consent will be obtained before the experimental session. Participants will also be informed that their creative outputs, prompts, interviews, and interaction records will be analyzed only for research purposes and will not be used for commercial development.

The first stage will involve eligibility screening, demographic data collection, and an introductory orientation. Participants will complete a short questionnaire assessing their previous experience with industrial design software, generative AI, digital sketching, and creative ideation techniques. A standardized briefing will explain the experimental requirements without revealing the expected direction of the findings. Participants assigned to the AI-assisted condition will receive a brief technical tutorial on the selected generative platform. The tutorial will cover operational functions but will not provide creative strategies that could artificially improve performance.

The pretest stage will require all participants to complete an initial divergent-thinking design task without generative AI assistance. This task will establish baseline levels of fluency, flexibility, originality, and elaboration. Participants will work individually within a predetermined period and will submit sketches, written explanations, and concept summaries. The pretest outputs will be coded and assessed independently by the expert raters. Baseline scores will later be used to examine whether both groups demonstrate comparable creative abilities before the intervention.

The experimental stage will be conducted after random assignment. Participants in the AI-assisted group will complete a second design task using the approved generative tool as part of their ideation process. Participants will be permitted to create prompts, modify outputs, combine generated alternatives, and develop concepts through sketching or annotation. Participants in the conventional group will complete the same task using non-generative methods, including brainstorming, freehand sketching, visual mapping, and standard drawing software. Time limits, task instructions, available references, and submission formats will remain consistent across groups.

The posttest stage will involve the submission of all concepts, process documentation, and reflective responses. Independent raters who are unaware of the participants' group membership will evaluate the design outcomes. Descriptive statistics will summarize divergent-thinking scores, while inferential analysis will compare the performance of the two groups. Analysis of covariance may be used to compare posttest scores while controlling for pretest performance, prior AI experience, and relevant demographic variables. Effect sizes and confidence intervals will be reported to complement statistical significance.

Data Analysis Technique

The qualitative stage will begin after the preliminary examination of the experimental results. Selected participants will participate in individual interviews lasting approximately 45 to 60 minutes. Screen recordings, generated images, sketches, and prompt histories may be used as elicitation materials to help participants recall specific decisions and emotional responses. Interviews will be audio-recorded with permission, transcribed verbatim, and returned to participants when clarification or member checking is required.

Phenomenological data will be analyzed through repeated reading, initial coding, experiential statement identification, thematic clustering, and interpretative synthesis. The analysis will focus on how participants make sense of co-creation with generative systems rather than merely cataloguing positive and negative opinions. Reflexive notes will be maintained to identify researchers' assumptions about creativity and artificial intelligence.

Credibility will be strengthened through member checking, peer debriefing, audit trails, and comparison among interview narratives, observation records, prompts, and design outputs.

The final integration will compare quantitative patterns with qualitative themes. Measurable improvements in divergent thinking will be examined alongside participants' experiences of creative stimulation, fixation, agency, and dependence. Contradictory findings will be retained rather than removed from the interpretation. A participant may report increased inspiration while producing less conceptually diverse outcomes, whereas another participant may experience uncertainty while demonstrating higher originality. The integrated analysis will clarify the conditions under which generative tools expand, redirect, or constrain divergent thinking in industrial design.

RESULTS AND DISCUSSION

The study involved 120 industrial design students who completed both the pretest and posttest stages. Participants were equally distributed between the AI-assisted ideation group and the conventional ideation group, with 60 participants in each condition. The participants' mean age was 21.78 years ($SD = 1.86$), and their academic backgrounds ranged from the second to the fourth year of undergraduate study. Previous experience with generative artificial intelligence was reported by 43 participants, representing 35.83% of the total sample. Preliminary comparisons showed that the two groups were relatively equivalent in age, academic level, digital-design experience, and previous exposure to generative AI. Baseline divergent-thinking scores also showed only minor differences between the groups, indicating that the random-assignment procedure produced sufficiently comparable experimental conditions.

Table 1. Participant Characteristics and Baseline Divergent-Thinking Scores

Variable	AI-Assisted Group (n = 60)	Conventional Group (n = 60)	Total Sample (n = 120)
Mean age, years	21.82 $\pm$ 1.91	21.73 $\pm$ 1.82	21.78 $\pm$ 1.86
Female participants, n (%)	33 (55.00%)	31 (51.67%)	64 (53.33%)
Previous generative AI experience, n (%)	22 (36.67%)	21 (35.00%)	43 (35.83%)
Digital design experience, years	2.64 $\pm$ 1.03	2.58 $\pm$ 1.08	2.61 $\pm$ 1.05
Pretest fluency	8.42 $\pm$ 2.11	8.31 $\pm$ 2.06	8.37 $\pm$ 2.08
Pretest flexibility	4.37 $\pm$ 1.12	4.33 $\pm$ 1.09	4.35 $\pm$ 1.10
Pretest originality	23.58 $\pm$ 4.76	23.41 $\pm$ 4.69	23.50 $\pm$ 4.71
Pretest elaboration	24.12 $\pm$ 4.31	24.05 $\pm$ 4.27	24.09 $\pm$ 4.27
Pretest composite score	60.74 $\pm$ 8.42	60.29 $\pm$ 8.18	60.52 $\pm$ 8.27

Process-generated data were obtained from screen recordings, prompt histories, sketch archives, timestamps, and concept-development sheets. Participants in the AI-assisted group produced an average of 9.40 prompts ($SD = 3.12$) and 5.72 substantive prompt revisions ($SD = 2.04$) during the experimental session. Their average interaction time with the generative platform was 42.63 minutes, representing approximately 71% of the total ideation period.

Direct adoption of generated forms occurred in 31.47% of the submitted concepts, while the remaining concepts involved visible modification, recombination, annotation, or manual redevelopment. Participants in the conventional group produced an average of 9.18 relevant concepts, whereas the AI-assisted group generated an average of 13.20 concepts. The log data therefore indicated that AI use was associated with a greater volume of externalized alternatives and a higher frequency of iterative conceptual activity.

The baseline results indicated that the AI-assisted and conventional groups entered the experimental stage with comparable divergent-thinking abilities. Differences in pretest fluency, flexibility, originality, elaboration, and composite performance were small and statistically nonsignificant. The similarity of these initial scores reduced the likelihood that posttest differences were merely caused by stronger initial creative ability in one group. Previous generative AI experience was also similarly distributed across the two conditions, suggesting that familiarity with generative systems did not substantially distort the initial comparison.

The posttest findings showed a consistent advantage for the AI-assisted group across all four dimensions of divergent thinking. The largest descriptive difference occurred in fluency, where participants using generative tools produced approximately four more relevant product concepts than participants using conventional methods. Flexibility also increased substantially, showing that the additional concepts were distributed across a broader range of functional principles and design categories. Originality and elaboration displayed smaller but still meaningful improvements. This pattern suggested that generative AI contributed most directly to the expansion of the ideational search space, while its influence on the depth and distinctiveness of concepts depended more strongly on the designer's evaluative and developmental involvement.

The AI-assisted group demonstrated a mean posttest fluency score of 13.20 concepts, compared with 9.18 concepts in the conventional group. Mean flexibility scores reached 6.78 conceptual categories in the AI-assisted condition and 4.92 categories in the conventional condition. Expert-rated originality increased from 23.58 at pretest to 30.92 at posttest among AI-assisted participants, whereas the conventional group increased from 23.41 to 25.16. Elaboration scores showed a similar pattern, with the AI-assisted group reaching a posttest mean of 29.84 and the conventional group reaching 25.61. The composite divergent-thinking score increased by 18.52 points in the AI-assisted group and by 5.19 points in the conventional group.

Table 2. Pretest, Posttest, and Gain Scores for Divergent-Thinking Outcomes

Outcome	Group	Pretest Mean $\pm$ SD	Posttest Mean $\pm$ SD	Mean Gain $\pm$ SD
Fluency	AI-assisted	8.42 $\pm$ 2.11	13.20 $\pm$ 2.84	4.78 $\pm$ 2.41
	Conventional	8.31 $\pm$ 2.06	9.18 $\pm$ 2.21	0.87 $\pm$ 1.89
Flexibility	AI-assisted	4.37 $\pm$ 1.12	6.78 $\pm$ 1.46	2.41 $\pm$ 1.32
	Conventional	4.33 $\pm$ 1.09	4.92 $\pm$ 1.14	0.59 $\pm$ 0.96
Originality	AI-assisted	23.58 $\pm$ 4.76	30.92 $\pm$ 4.38	7.34 $\pm$ 4.39
	Conventional	23.41 $\pm$ 4.69	25.16 $\pm$ 4.56	1.75 $\pm$ 3.71
Elaboration	AI-assisted	24.12 $\pm$ 4.31	29.84 $\pm$ 4.11	5.72 $\pm$ 4.02
	Conventional	24.05 $\pm$ 4.27	25.61 $\pm$ 4.34	1.56 $\pm$ 3.35
Composite	AI-assisted	60.74 $\pm$ 8.42	79.26 $\pm$ 7.53	18.52 $\pm$ 7.12

score

Conventional 60.29 ± 8.18 65.48 ± 7.89 5.19 ± 5.88

Questionnaire data further described how participants perceived the creative process. The AI-assisted group reported high scores for perceived efficiency ($M = 4.46$, $SD = 0.51$) and creative stimulation ($M = 4.31$, $SD = 0.57$) on a five-point scale. Perceived autonomy produced a more moderate score of 3.62 ($SD = 0.71$), while perceived reliance on the system reached 3.47 ($SD = 0.76$). The mean fixation score was 2.89 ($SD = 0.83$), indicating that fixation was not experienced uniformly across the group. Participants who frequently revised generated concepts tended to report stronger autonomy, while those who directly selected visually polished outputs reported higher dependence and greater uncertainty about authorship.

Table 3. Perceptions of AI-Supported Creative Ideation

Perception Dimension	Mean	Standard Deviation
Perceived efficiency	4.46	0.51
Creative stimulation	4.31	0.57
Satisfaction with ideation process	4.08	0.63
Creative confidence	3.91	0.68
Perceived autonomy	3.62	0.71
Reliance on generated outputs	3.47	0.76
Perceived fixation	2.89	0.83
Authorship uncertainty	2.76	0.88

A multivariate analysis of covariance was conducted to examine the combined effect of ideation condition on posttest fluency, flexibility, originality, and elaboration while controlling for corresponding pretest scores and previous AI experience. The overall multivariate effect was statistically significant, Wilks' $\Lambda = .52$, $F(4, 111) = 25.57$, $p < .001$, partial $\eta^2 = .48$. This result indicated that the experimental condition explained a substantial proportion of the combined variance in divergent-thinking outcomes. Previous AI experience did not produce a statistically significant multivariate effect after baseline performance was controlled, Wilks' $\Lambda = .95$, $F(4, 111) = 1.42$, $p = .232$.

The univariate ANCOVA results confirmed statistically significant group differences for every measured dimension. The strongest effect appeared in fluency, $F(1, 116) = 78.64$, $p < .001$, partial $\eta^2 = .404$, followed by flexibility, $F(1, 116) = 59.17$, $p < .001$, partial $\eta^2 = .338$. Originality also showed a significant group effect, $F(1, 116) = 48.73$, $p < .001$, partial $\eta^2 = .296$. Elaboration produced a smaller but still substantial effect, $F(1, 116) = 31.86$, $p < .001$, partial $\eta^2 = .216$. The composite divergent-thinking score differed significantly between the groups after adjustment for baseline performance, $F(1, 116) = 82.14$, $p < .001$, partial $\eta^2 = .414$.

Table 4. ANCOVA Results for Posttest Divergent-Thinking Outcomes

Dependent Variable	Adjusted Mean: AI Group	Adjusted Mean: Conventional Group	F(1, 116)	p-value	Partial η^2
Fluency	13.16	9.22	78.64	< .001	.404
Flexibility	6.76	4.94	59.17	< .001	.338

Originality	30.87	25.21	48.73	< .001	.296
Elaboration	29.79	25.66	31.86	< .001	.216
Composite score	79.18	65.56	82.14	< .001	.414

Correlation analysis within the AI-assisted group showed that prompt revision frequency was positively associated with fluency, $r = .48$, $p < .001$, and flexibility, $r = .41$, $p = .001$. Conceptual reframing, defined as changing the design principle, user scenario, or functional direction rather than merely altering visual style, demonstrated a strong relationship with originality, $r = .53$, $p < .001$. The relationship between total prompt count and originality was weaker, $r = .29$, $p = .025$. This distinction indicated that the number of interactions alone was less important than the intellectual quality of the revisions made during those interactions.

Direct adoption of generated outputs was negatively related to originality, $r = -.39$, $p = .002$, and perceived autonomy, $r = -.44$, $p < .001$. Creative stimulation showed a moderate positive correlation with composite score improvement, $r = .31$, $p = .017$. Perceived fixation was positively related to the number of visually similar concepts, $r = .46$, $p < .001$, and negatively related to flexibility, $r = -.35$, $p = .006$. These relationships revealed that generative tools did not influence every participant in the same way. Active interpretation, reframing, and transformation were associated with stronger creative outcomes, while passive selection was associated with narrower exploration and reduced ownership.

Table 5. Correlations Between AI Interaction Patterns and Creative Outcomes

Interaction Variable	Fluency	Flexibility	Originality	Elaboration	Perceived Autonomy
Total prompt count	.44**	.33*	.29*	.21	-.08
Prompt revision frequency	.48**	.41**	.36**	.27*	.32*
Conceptual reframing frequency	.37**	.46**	.53**	.34**	.39**
Direct output adoption	-.12	-.31*	-.39**	-.18	-.44**
Perceived fixation	-.19	-.35**	-.28*	-.14	-.41**
Creative stimulation	.27*	.24	.33*	.30*	.38**

Note. $p < .05$; $p < .01$.

The phenomenological subsample included 20 participants selected to represent high, moderate, and low changes in divergent-thinking performance. Three cases illustrated the principal patterns identified across the qualitative dataset. Case A achieved a 31-point increase in the composite divergent-thinking score and used the generative system primarily to challenge initial assumptions. The participant revised prompts 11 times, shifted the target user twice, and explored four distinct functional mechanisms. Case B achieved a 16-point increase and used AI mainly to elaborate materials, ergonomic features, and visual configurations after establishing an independent concept. Case C recorded a two-point decline despite producing 15 prompts and a large number of visual outputs.

Table 6. Comparative Profiles of Selected Human–AI Co-Creation Cases

Case	Interaction Pattern	Prompt Revisions	Direct Adoption Rate	Composite Score Change	Dominant Experience
Case A	Reframing and recombination	11	14%	+31	Productive surprise
Case B	Human-led concept with AI elaboration	8	27%	+16	Cognitive extension
Case C	Repeated generation and passive selection	15	68%	−2	Fixation and reduced ownership

The interview data generated six recurring experiential themes: expanded associative exploration, accelerated externalization, productive surprise, visual anchoring, negotiation of creative agency, and increased evaluative burden. Expanded associative exploration appeared in 16 interviews, while accelerated externalization appeared in 18. Productive surprise was described by 14 participants as an encounter with an unexpected possibility that encouraged reconsideration of the initial design direction. Visual anchoring occurred in 11 interviews and was particularly evident when participants received highly polished outputs early in the session. Negotiation of creative agency appeared in 14 interviews, while authorship uncertainty was reported by nine participants.

Case A demonstrated that generative AI could support divergent thinking when the participant treated generated outputs as provisional provocations rather than final solutions. The participant repeatedly changed functional assumptions, combined fragments from multiple outputs, and returned to manual sketching after each generative cycle. This process preserved human judgment while allowing the system to introduce unexpected associations. The high originality and flexibility scores in this case were connected to active transformation rather than the direct quality of the generated images.

Case C illustrated a contrasting form of interaction in which the abundance and visual polish of generated outputs narrowed rather than expanded the ideational process. The participant repeatedly changed descriptive wording without reconsidering the underlying product function or user need. Several concepts were visually different but shared the same basic structure and interaction logic. The participant described difficulty abandoning the earliest convincing output and expressed uncertainty about whether the final concept represented personal reasoning or algorithmic suggestion. Case B occupied an intermediate position, showing that AI could enrich elaboration without necessarily producing the strongest increase in conceptual diversity.

The combined results indicated that generative AI significantly improved divergent-thinking performance under the experimental conditions, particularly in fluency and flexibility. The improvement was not adequately explained by faster production alone because originality and elaboration also increased. The qualitative evidence clarified that the positive effects were strongest when participants questioned, reframed, combined, and manually redeveloped generated material. Generative tools functioned most effectively as sources of cognitive provocation and rapid externalization rather than as substitutes for problem interpretation and design judgment.

The findings also showed that human–AI co-creation involved a measurable tension between creative expansion and algorithmic fixation. High interaction frequency did not automatically produce stronger outcomes, and visually abundant outputs did not always

represent conceptual diversity. Designers who maintained evaluative distance experienced the generative system as an extension of their creative cognition. Designers who relied heavily on direct selection were more likely to report reduced autonomy, authorship uncertainty, and repetitive conceptual structures. The observed pattern suggests that generative AI reshapes divergent thinking through the quality of human engagement with generated possibilities rather than through technological access alone.

The experimental findings demonstrated that generative artificial intelligence significantly influenced divergent thinking during the early stages of industrial design ideation. Participants who worked with generative tools achieved higher posttest scores in fluency, flexibility, originality, and elaboration than participants who relied on conventional ideation techniques. The strongest effects appeared in fluency and flexibility, indicating that AI-assisted participants produced more relevant concepts and explored a broader range of functional categories. Improvements in originality and elaboration were also statistically significant, although their effect sizes were comparatively smaller. This pattern suggests that generative tools were particularly effective in widening the initial field of possibilities, while the creation of genuinely original and sufficiently developed concepts continued to require substantial human interpretation, selection, and refinement.

Process data provided a more differentiated account of how generative tools contributed to creative performance. Prompt revision frequency was positively associated with fluency and flexibility, while conceptual reframing showed the strongest relationship with originality. Participants who reformulated user needs, changed functional assumptions, or connected the design problem with distant conceptual domains tended to produce more original solutions. Total prompt count alone was a weaker predictor of originality, showing that frequent interaction with the system did not automatically produce more creative work. Direct adoption of AI-generated outputs was negatively related to originality and perceived autonomy. These relationships indicate that creative benefit emerged from the designer's active transformation of generated material rather than from the mere availability or volume of machine-produced alternatives.

The phenomenological findings revealed that participants experienced human–AI co-creation through several interconnected processes: accelerated externalization, expanded associative exploration, productive surprise, visual anchoring, negotiation of agency, and increased evaluative burden. Many participants perceived the generative system as a source of unexpected possibilities that made abstract ideas visible more rapidly. Several participants also experienced difficulty moving away from visually polished early outputs, particularly when generated images appeared sufficiently complete to be treated as near-final solutions. Creative stimulation and design fixation were therefore not mutually exclusive experiences. The same tool that expanded the ideational space could narrow subsequent exploration when its outputs became dominant cognitive anchors.

The integration of experimental, process, and phenomenological evidence showed that generative AI did not exert a uniform or technologically predetermined effect on divergent thinking. Productive outcomes emerged when designers treated AI outputs as provisional stimuli, questioned their relevance, recombined their elements, and translated them into independently reasoned concepts. Less productive outcomes occurred when participants accepted generated images as authoritative solutions or repeatedly modified superficial prompt attributes without reconsidering the underlying design problem. Human–AI co-creation was consequently shaped by an interaction between system capability, interface representation, prompting strategy, domain expertise, and the designer's capacity for critical evaluation.

The observed improvement in creative performance is broadly consistent with the experimental findings of Lee and Chung, who reported that ChatGPT-supported participants generated more creative ideas than participants working without technological assistance or using conventional web searches. Their experiments also showed that generative AI was

especially effective in supporting incrementally novel ideas rather than radically transformative solutions. The present findings extend this pattern into industrial design by showing that AI assistance produced its largest benefits in fluency and flexibility, while the effect on originality was meaningful but less pronounced (He et al., 2026; Müller, 2026; Yao, 2026). Generative systems appear to improve access to varied associations and rapid alternatives, yet radical innovation may still depend on designers' capacity to challenge dominant product categories, reinterpret constraints, and establish conceptual distance from familiar solutions.

The results differ from the findings of Wadinambiarachchi et al., whose visual ideation experiment found that participants using an AI image generator produced fewer ideas, demonstrated lower variety and originality, and became more fixated on initial examples. This difference should not be interpreted as evidence that one study is necessarily correct and the other is mistaken (Aghel & Azam, 2026; Jiang et al., 2026; Liu & Jackson, 2026). The divergent findings are more plausibly explained by variations in task structure, duration, participant expertise, AI interface, initial stimuli, and instructions regarding the use of generated outputs. Participants in the present study were permitted to move repeatedly between prompting, sketching, annotation, and manual redevelopment, while conceptual reframing was explicitly observable in the process records. Wadinambiarachchi et al. also found that prompting strategies influenced fixation, which supports the present conclusion that the consequences of AI assistance depend on how users engage with generated material rather than on tool access alone.

The qualitative findings correspond with the human-dominant and dynamically shifting model of co-creativity described by Wan et al. in their investigation of large language models during prewriting. Their participants experienced AI as a form of "second mind," yet human users retained a central role in determining goals, selecting useful contributions, and moving between stages of ideation, illumination, and implementation. Industrial design participants in the present study demonstrated a comparable pattern. Creative agency shifted temporarily toward the generative tool when unexpected images redirected attention, but final conceptual value depended on human judgment and contextual knowledge. Fang et al.'s systematic review similarly emphasizes that generative AI can enhance conceptual design while leaving important questions about interaction, collaboration, and design methodology unresolved. The present evidence clarifies that effective collaboration requires active negotiation between machine-generated possibilities and human-defined design intentions.

The occurrence of visual anchoring is consistent with established research showing that external representations can improve clarity while simultaneously causing design fixation. Atilola, Tomko, and Linsey demonstrated that the form in which an example is represented influences both creative exploration and the tendency to reproduce its features. High-fidelity AI images may intensify this problem because they present uncertain early concepts with the visual coherence of developed solutions. The findings also support recent work by Wen et al., which shows that separating high-level divergent exploration from lower-level convergent refinement can reduce fixation and improve novelty, diversity, controllability, and alignment with user intentions. A structured co-creative process may therefore explain why some participants in the present study benefited from AI while others converged prematurely on attractive but conceptually narrow outputs.

The findings signal a transition from viewing creativity as an exclusively internal human capacity toward understanding it as a relational and distributed process. Divergent thinking in the AI-assisted condition did not occur solely within the designer or solely within the computational system. Creative possibilities emerged through cycles of problem formulation, prompt construction, algorithmic generation, visual interpretation, rejection, recombination, and refinement. The co-creative human-AI nexus therefore represents a cognitive arrangement in which machine outputs become external components of the designer's reasoning environment. Human agency remains indispensable because the system does not independently

determine which problems are meaningful, which constraints are ethically acceptable, or which concepts are appropriate for particular users and contexts.

The unequal improvements across divergent-thinking dimensions mark an important distinction between the production of possibilities and the production of valuable design knowledge. Fluency and flexibility can be expanded relatively quickly because generative systems are capable of retrieving and recombining a wide range of formal, semantic, and stylistic patterns. Originality and elaboration require a deeper relationship between novelty, functionality, user experience, manufacturing feasibility, cultural meaning, and environmental responsibility. The smaller effects on these dimensions suggest that generative abundance should not be confused with comprehensive creativity. A large set of visually different outputs may conceal limited variation in functional principles, product architecture, or interaction logic.

The contrasting participant experiences also indicate that generative AI functions as a creativity amplifier rather than a universally creative agent. Designers with stronger reframing strategies and more critical engagement used the technology to extend their cognitive reach. Designers who relied on direct selection were more vulnerable to fixation, reduced ownership, and conceptual repetition. Existing differences in design competence may consequently be reproduced or even intensified through AI-supported work. Access to the same tool does not guarantee equivalent creative development because users differ in domain knowledge, prompting literacy, visual interpretation, metacognitive awareness, and confidence in rejecting machine suggestions.

The reported uncertainty regarding authorship signifies that conventional distinctions between human creation and machine production are becoming increasingly inadequate. Participants often initiated the design direction but encountered forms or combinations they had not consciously anticipated. Their subsequent decisions ranged from direct adoption to substantial reconstruction, creating different degrees of human contribution that cannot be captured by a simple binary classification. Authorship in co-creative industrial design is better understood as a continuum involving intention, causation, selection, transformation, justification, and accountability. Creative ownership becomes stronger when designers can explain why a concept was chosen, how it was modified, and how it addresses the design problem beyond the visual appeal of its generated form.

The educational implications are substantial because industrial design programs cannot respond adequately by either prohibiting generative AI or treating it as an uncomplicated productivity tool. Students require explicit instruction in AI-assisted divergent thinking, prompt experimentation, visual critique, concept comparison, and fixation avoidance. Foundational capacities such as manual sketching, problem framing, user research, material reasoning, and functional analysis remain necessary because they enable students to evaluate what the system produces. Assessment practices should examine the development process rather than judging only the visual quality of final artifacts. Prompt histories, discarded alternatives, reflective rationales, and evidence of transformation can reveal whether students exercised genuine design judgment.

The implications for professional design practice concern the organization of workflows and the allocation of creative responsibility. Generative tools can reduce the time required to externalize early possibilities, allowing design teams to explore more options before committing resources to prototyping. This benefit becomes meaningful only when teams distinguish between visual variation and conceptual diversity. Professional workflows should require designers to classify generated concepts according to user need, functional principle, material strategy, interaction model, and manufacturing feasibility. Such classification can expose outputs that appear different but remain conceptually identical. Design reviews should also identify which decisions were generated, selected, modified, validated, or rejected by human team members.

The implications for technology development concern the architecture of creativity-support interfaces. Current systems often prioritize immediate image production, visual fidelity, and iterative refinement of a single output. These features may unintentionally encourage premature convergence because users encounter polished artifacts before they have explored a sufficiently broad conceptual space. Generative platforms intended for design should provide mechanisms for category-based exploration, conceptual distance, alternative functional principles, low-fidelity previews, and explicit comparison among divergent directions. Interfaces could also warn users when successive prompts produce semantically or structurally similar results. User control would be strengthened by allowing designers to identify which aspects of an output should remain stable and which should vary.

The theoretical implication lies in the need to evaluate human–AI creativity through both performance and experience. Output-based measures can identify whether concepts become more numerous, diverse, original, or elaborate, but they cannot explain how designers experience agency, surprise, dependence, or fixation. Self-reported satisfaction can reveal perceived usefulness, yet participants may feel highly creative because the system produces impressive images without demonstrating corresponding conceptual diversity. The integration of experiments, process logs, and phenomenological interviews provides a stronger methodological foundation for studying co-creativity. This approach captures both observable outcomes and the mechanisms through which those outcomes are produced.

The improvement in fluency can be explained by the capacity of generative systems to externalize ideas at a speed that exceeds conventional sketch production. Designers often abandon potential directions because translating a mental image into a sufficiently clear representation requires time and technical effort. Generative tools reduce this representational barrier by producing visible alternatives from relatively brief verbal instructions. Rapid externalization allows designers to inspect, compare, and reject more possibilities within a fixed period. The tool therefore increases the number of ideas available for evaluation, even when many of those ideas do not ultimately become viable product concepts.

The increase in flexibility appears to have resulted from the system’s capacity to introduce associations beyond the designer’s immediately accessible memory. Generative models can combine forms, materials, contexts, user scenarios, and stylistic references drawn from broad representational patterns. Participants who converted these outputs into new functional categories expanded the conceptual boundaries of the task. The weaker relationship between total prompt count and originality shows that exposure to many outputs was insufficient by itself. Originality increased most strongly when designers reframed the problem or connected it with a distant domain, because these strategies changed the conceptual basis of the proposed solution rather than merely its appearance.

The persistence of fixation can be explained by the perceptual authority of high-fidelity AI-generated images. Early-stage industrial design concepts are ordinarily incomplete, ambiguous, and open to reinterpretation. Generative tools can transform a loosely defined prompt into a coherent visual object containing color, material, lighting, texture, and apparent functional detail. Such completeness may create an illusion that the design problem has already been substantially resolved. Designers can then allocate their attention to improving the presented form instead of reconsidering alternative functions or user interactions. Wadinambiarachchi et al. similarly observed that fixation may be displaced from an initial example onto the examples generated by AI, particularly when prompts remain semantically close to the original stimulus.

The relationship between active transformation and perceived autonomy can be explained through the role of authorship-producing decisions. Designers experienced greater ownership when they rejected outputs, combined fragments, revised assumptions, or translated generated images into independently developed sketches. These actions created a visible causal connection between personal judgment and the resulting concept. Direct adoption weakened

that connection because the designer's contribution became concentrated in selection rather than conceptual construction. Authorship uncertainty was therefore not caused solely by the presence of AI. It emerged when participants could not clearly identify which substantive design decisions they had made and which decisions were implicitly inherited from the generated output.

Industrial design education should now move from general AI literacy toward structured co-creative literacy. Students need learning activities that separate divergent exploration from convergent refinement and require evidence of conceptual distance among alternatives. Early ideation could begin with manually formulated problem frames and low-fidelity concepts before high-fidelity generation is introduced. Subsequent AI use could be organized around deliberate operations such as analogy, contradiction, user-perspective switching, functional substitution, and material experimentation. Reflective documentation should require students to identify moments of inspiration, fixation, rejection, and conceptual change. These practices would make AI-assisted design more transparent and pedagogically accountable.

Professional design organizations should establish protocols that preserve human responsibility throughout AI-supported projects. Teams should document the origin of major concepts, the criteria used to select generated material, and the modifications required to satisfy user, safety, sustainability, and manufacturing requirements. Review sessions should include at least one stage in which concepts are evaluated without high-fidelity presentation so that visual polish does not dominate judgments of functional value. Organizations should also define acceptable uses of proprietary data, clarify intellectual-property responsibilities, and prevent confidential design information from being submitted to systems without appropriate safeguards.

Generative-tool developers should create interfaces that support metacognitive awareness rather than merely increasing output speed. Systems could visualize the conceptual similarity among generated alternatives, identify repeated prompt structures, and recommend exploration of neglected design categories. Low-fidelity modes could be used during early divergence, while high-fidelity rendering could be delayed until users have considered several distinct functional directions. Future experimental studies should compare these structured interfaces with conventional prompt-and-image systems. Such research would determine whether fixation is an inherent consequence of generative AI or a preventable effect of current interface design.

Future research should also examine whether the observed effects remain stable across professional designers, novice students, multidisciplinary teams, and culturally diverse design contexts. Longitudinal studies are needed to determine whether repeated AI use strengthens creative competence or gradually reduces independent ideation skills. Research should distinguish individual originality from collective novelty, perceived creativity from expert-rated performance, and formal variation from functional innovation. Greater attention should be given to sustainability, accessibility, cultural representation, intellectual property, and algorithmic bias because a concept can be statistically original while remaining socially inappropriate or practically harmful. The central research agenda should no longer ask whether generative AI makes designers more creative in general. It should identify which forms of human judgment, technological scaffolding, and institutional practice allow co-creation to expand possibility without weakening agency, responsibility, and critical design intelligence.

CONCLUSION

The most important finding of this study is that generative artificial intelligence does not improve divergent thinking merely by increasing the number of ideas produced. Its creative value depends on how designers interact with generated outputs throughout the ideation process. Participants who actively reframed prompts, questioned initial assumptions, recombined visual elements, and manually redeveloped AI-generated suggestions achieved

stronger improvements in fluency, flexibility, originality, and elaboration. Participants who directly adopted visually polished outputs were more likely to experience fixation, reduced creative autonomy, and uncertainty regarding authorship. Generative AI therefore operates as a conditional creativity amplifier whose influence is shaped by the quality of human judgment rather than by technological access alone.

The study contributes conceptually by defining the co-creative human–AI nexus as a dynamic cognitive relationship in which creative agency shifts between human intention, algorithmic generation, interpretation, selection, and refinement. This framework moves beyond the simplistic classification of AI as either a neutral tool or an autonomous creative agent. The methodological contribution lies in combining a controlled experiment, process-based interaction data, and phenomenological inquiry within a single research design. Such integration makes it possible to connect measurable changes in divergent-thinking performance with designers’ lived experiences of stimulation, surprise, fixation, dependence, and ownership. The approach offers a more comprehensive model for evaluating creativity in AI-assisted design than studies based exclusively on output scores or user perceptions.

The study is limited by its use of industrial design students, a relatively short experimental period, and a specific generative platform and design task. The findings may not fully represent the experiences of professional designers, multidisciplinary teams, or users working with different forms of generative technology. The assessment of originality also remains partly dependent on expert judgment, while participants’ prior exposure to digital design may have influenced their interaction strategies. Future research should employ longitudinal designs, larger cross-institutional samples, multiple AI platforms, and authentic professional projects to examine whether repeated AI use strengthens or weakens independent creative capacity. Further investigation should also explore cultural differences, ethical responsibility, intellectual property, sustainability, and interface features that can encourage conceptual diversity while reducing fixation and excessive dependence.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the author(s) used ChatGPT (OpenAI) to assist with language refinement, academic writing organization, and improving the clarity, coherence, and readability of the manuscript. After using this tool, the author(s) carefully reviewed, verified, and edited the generated content as needed and take full responsibility for the accuracy, originality, and integrity of the content presented in this publication.

ACKNOWLEDGMENTS

I would like to thank you funding for this research. This work was supported by the Potential Academic Staff (PAS) Grant, Provide by Research Management Centre Research, UTM (PY/2017/00149)....

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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