Design Science

Design•AI: a study of practice-based integration of AI as a creative partner in design

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Abstract

As AI continues to evolve and demonstrate new design capabilities, there is an opportunity to explore its integration with design at a process level. While recent studies have examined the creative potential of AI-based design tools and their use in enhancing individual tasks, there remains an opportunity to understand how the design process might evolve at the end-to-end design workflow macro scale through study of practice-based design. We follow a revised design process workflow, alongside an exemplar implementation using interactive digital workspaces, establishing an applied approach for viewing the design process as a dialogue between humans and AI. Data were collected from three-day continuing education workshops with industry professionals, providing an empirical dataset that offers longitudinal insights into how the proposed workflow performs in real-world contexts. The approach is evaluated through method-level comparisons and a longitudinal study providing process-level evaluation between human-only and AI-augmented workshop flows, comprising four workshops and 20 teams. Two methods, affinity clustering and mind mapping, were sampled for direct comparison. Participants preferred the AI-augmented workflow, and method-level comparisons indicate comparable quality. The primary contribution is a practice-based, longitudinal account of integrating AI across an end-to-end professional design workflow.

Keywords: Design Innovation, Artificial Intelligence, Creativity, Design Process, Design Methods, Design Theory, Human AI Interaction

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1. Introduction

1.1. Emergence of AI

Artificial Intelligence (AI) is reshaping the way we work, study, and design (Russell & Norvig 2016; Brynjolfsson & McAfee 2017). AI has surpassed many of the limitations of early machine learning and computer vision approaches, enabling greater efficiency and effectiveness across numerous fields, including design. State-of-the-art AI tools perform a broad range of cognitive tasks, including text and image analysis, text generation, and image generation (Brown *et al.* 2020; Feuerriegel *et al.* 2024).

There are many controlled studies exploring the implementation of AI in the design process, comparisons of ideation, innovation, and research with and without AI/ML (Chen *et al.* 2019; Koch *et al.* 2019; Rahman *et al.* 2020; Jeon *et al.* 2021; Sarica *et al.* 2021; Siddharth, Blessing, & Luo 2022; Zhu & Luo 2022;

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Cai *et al.* 2023; Cheng 2023; Wan & Lu 2023; Bouschery, Blazevic, & Piller 2024; Ghasemi *et al.* 2024; Guo, Pataranutaporn, & Maes 2024; Norheim *et al.* 2024; Papachristos *et al.* 2024; Sarica & Luo 2024; Wadinambiarachchi *et al.* 2024; Chong *et al.* 2025; Feng, Hélie, & Panchal 2025; Kokate & Onkar 2026), as a collaborative agent (Karimi *et al.* 2020; Lin *et al.* 2020; Kim, Maher, & Siddiqui 2021; Siemon 2022; Lavrič & Škraba 2023; Shin *et al.* 2023; Muller *et al.* 2024; Nomura, Ito, & Ding 2024), approaches to optimise the output of AI results (Ge *et al.* 2025; Meincke, Mollick, & Terwiesch 2024), to foster iteration (Zhou *et al.* 2020), to provide ideation stimulus (Li *et al.* 2021; Kim & Maher 2023; Kwon, Rao, & Goucher-Lambert 2023; Wang & Han 2023; Ranscombe *et al.* 2024), evaluate design reliability through FMEA (El Hassani *et al.* 2025) or support 3D modelling (Castro Pena *et al.* 2021; Li, Xie, & Sha 2023), even design course planning (Meron & Araci 2023), and novel AI-augmented methods that enhance design quality in specific activities such as TRIZ and bio-inspired design (Zhu & Luo 2023; Zhu, Zhang, & Luo 2023; Siddharth & Luo 2024; Jiang *et al.* 2025; Ren, Ma, & Luo 2025). In parallel, recent studies compare human and AI performance in design generation and highlight emerging challenges for data-driven design (Chen *et al.* 2025; Monti *et al.* 2025; Vo 2025). More recent work reviews studies of AI use across the full design-thinking cycle and frames it as a co-designer spanning divergent and convergent phases (Mirzaei *et al.* 2026), diagnoses stagnation in problem framing and solution development across design project phases (Ito *et al.* 2026), and advances LLM-driven ideation methods evaluated against human and computational creativity measures (Tanaka, Nomaguchi, & Fujita 2026). Others formalise aggregation functions for ideation metrics such as variety, novelty, and quality (Sorensen *et al.* 2026), and recast idea evaluation itself as a generative process of managing fixation and defixation (Boudier *et al.* 2023). At the same time, studies caution that AI-assisted ideation may dampen cognitive engagement and erode novice designers' creative confidence, raising concerns of over-reliance (Krajcer *et al.* 2026). Overall, these studies show that under the right conditions, AI can be used to enhance creativity and offers significant promise for benefiting the future of design. While many prior works investigate the potential of AI for specific design tasks, the present study adopts a preliminary system-level perspective, opening a discussion on how AI integrates across the full design process and how designers may derive value from this emerging collaboration.

As the research group behind this paper is involved in frequent design thinking workshops for professionals, it was possible to develop and comparatively evaluate a modified design thinking approach with and without AI intervention. The core research questions extend the emerging body of work on AI applied to specific design tasks by examining process-level integration of AI through the following research questions:

1. How does integrating AI across the full design workflow – from problem definition through prototyping – affect participant preference compared to a human-only process?
2. Within sampled design methods, are AI-augmented outcomes of comparable quality to human-generated results, such that AI integration would not be expected to degrade those steps?

We propose that AI can function as a co-designer, expanding human capabilities at each phase of the design thinking process. This integration combines

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human designers' contextual insights and holistic reasoning with AI's ability to rapidly analyse and organize data, as well as draw from prior knowledge to generate new ideas or support critical design research tasks such as user needs analysis. This study spans over 5,000 person-hours dedicated to design workshops (including professional participants' commitment).

The Triple Diamond model Figure 1 represents one possible evolution of the traditional 4D process, where AI accelerates iteration, augments exploration, and facilitates multiple design cycles within each phase. AI can expand or refine human inputs – such as questions, directions, or concept sketches – thereby extending knowledge and enabling smoother, more connected transitions across stages of the design process. While AI enhances creativity and speed, decision-making remains human-led, ensuring thoughtful integration of AI augmentation within design education and practice.

This study explores a practical implementation of an integrated design and AI workflow through an evaluation of design thinking workshops, comparing key design methods conducted with and without AI support. To establish the rationale for this work, we first provide a brief introduction to the overarching objectives of Design Innovation (Design Council 2005; Camburn *et al.* 2017; Sheppard *et al.* 2018; Cross 2023), followed by a detailed breakdown of the proposed integrated design and AI workflow. Finally, we review the methods and results of an experimental evaluation, examining the implementation across a series of professional development workshops.

1.2. Importance of DI

A structured approach to design can facilitate finding more innovative solutions via integration of best practices observed through experimentation and industry design studies. Design Innovation (DI) is a process framework encompassing design thinking, business design, systems engineering, and design engineering (Camburn *et al.* 2017). DI follows the 4D Triple Diamond model, derived from the UK Council's "4D" model of design, which consists of four phases (Design Council 2005):

1. *Discover* – Engage various stakeholders to understand their needs.
2. *Define* – Analyse user data to identify and reframe opportunities.
3. *Develop* – Generates ideas or solutions in textual or visual form, then down-selects. Based on desirability, viability, and feasibility.
4. *Deliver* – Produce prototypes and test solutions with users, iterating for improvement.

Design also relies on key principles or strategic mindsets which may enhance process outcomes and are continuously integrated into the process. For instance, at McKinsey & Company, the value of design is structured principles such as Analytical Leadership, Cross-functional Talent, User Experience, and Continuous Iteration (Sheppard *et al.* 2018). The DI methodology framework, developed at SUTD and implemented through in-person, studio-style workshops where teams create content collaboratively using interactive web-based collaborative media boards, also incorporates several key principles, as illustrated by the following examples (Camburn *et al.* 2017):

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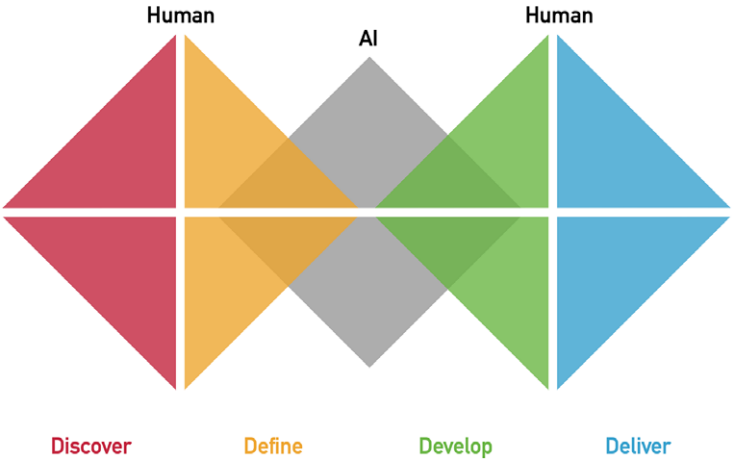


Figure 1. Design•AI Tri-Diamond, a modified design process flowchart. Illustrates the integration impact of AI in the design process; humans set intention and guide selection, AI accelerates and supports development efforts (reproduced from Camburn & Koh 2026).

- *Creativity Throughout* – innovation requires creative thinking not just in generating solutions, but in identifying needs, framing opportunities, or strategically planning early prototypes.
- *Empathy for all* – empathy is a core component of design, as ultimately solutions must address human problems.
- *Make, Test, Learn, Repeat* – early testing is critical to long-term success, to refine requirements and identify failure points early in the process rather than later.

Figure 2 presents a snapshot from a digital collaboration board used by teams to document, organize, and present design results during typical 3–5 day workshops. This template systematically guides teams through the full design innovation sprint, covering Discover, Define, Develop, and Deliver, along with their respective methods.

These workshops are organized by the Design Innovation Office at the Singapore University of Technology and Design (SUTD), within the SUTD Academy research centre. The DI team has been active in Singapore for over 12 years, training thousands of design professionals in Design Innovation methodology.

2. Example AI-augmented design workflow

The approach presented in this paper represents Figure 1 is a synthesis of best practices identified in design and AI literature, combined with insights from the team's practical experience and iterative efforts to integrate design and AI into innovation training. A particular instance of this approach is illustrated in Figure 3 where the sequence of methods introduced in each workshop is presented, along with callouts indicating where AI-augmented activities have been injected to support the process.

AI can support design as a tool to expand the possible number of interactions and refinements at each stage. It supports expanding the design space; thus, this

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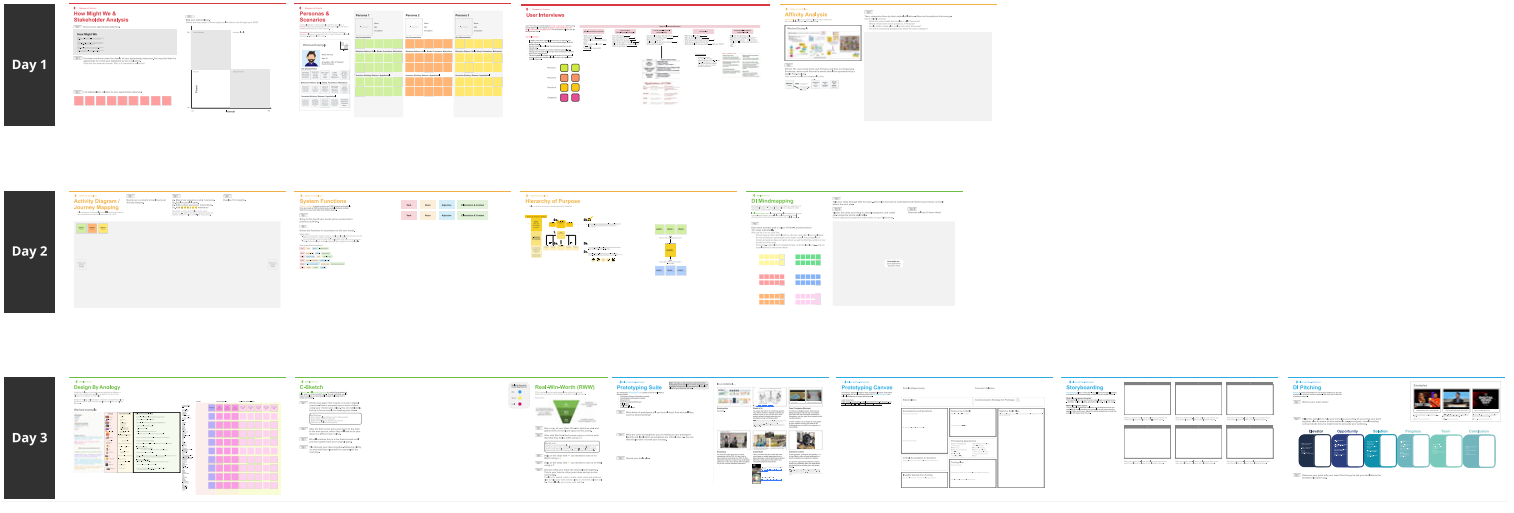


Figure 2. Design innovation template commonly used in SUTD Academy workshops. Overview of a typical workshop activity flow; completed samples of selected individual methods are provided below.

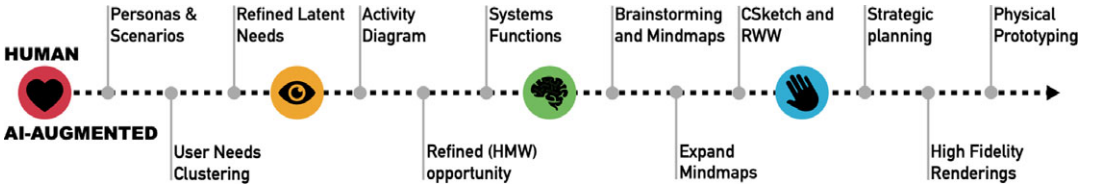


Figure 3. Applied sequence of design methods, contrasting AI- and human-driven methods. The design process evolves as a "dialogue" between human and AI agents.

figurative exploration provides a basis for the approach of formally introducing AI in specific methods as we demonstrated in Table 1. In each phase, human designers always develop initial insights first before AI is engaged to expand or organize results to reduce potential fixation on the initial AI-generated results. Table 1 details the applied methods within each design phase, as well as a description of how each method is conducted with strictly human-generated results versus human–AI collaboration. The following sections provide further details and sample content from each phase.

Table 1. Detailing of the human–AI collaboration methods in the AI-Augmented workshop flow

Method	Description of the method
Personas and scenarios	A Persona represents a typical or extreme user, summarising real behaviour patterns into archetypes. Scenarios describe the context of use and user needs. Human designers create Personas; the AI designer generates Scenarios from each Persona (AI may also support with image-renders of personas or scenarios).
Affinity analysis	An Affinity Diagram groups ideas by natural relationships. Human designers extract user needs from Scenarios; the AI designer clusters them into groups based on similarity.
Activity diagram	An activity diagram is a block diagram of sequential and parallel activities that capture user interactions with a product, service or system.
System functions	A System Functions Model is a representation of a Product, Service or System (PSS) used to create functions for the PSS.
Hierarchy of purpose	Hierarchy of Purpose refines design opportunity statements through iterative rewriting. Human designers form generic statements; the AI designer specifies them further.
Mind mapping	Mind mapping organizes ideas hierarchically from topic to sub-idea. Human designers brainstorm and map ideas; the AI designer adds related ideas to expand the map (AI may also augment through deep research and reclustering).
C-Sketch	Collaborative sketching, or C-sketch, is a rapid way to generate and build upon the ideas that you and your team members have.
Real-win-worth	Real? Win? Worth it? is a method to manage risk and reward. It provides a way to rapidly assess the marketability of an innovation by asking a series of questions.
Prototyping	Includes Prototyping Canvas, Mock-ups, Paper Prototypes, Wireframes, Role-playing, Wizard-of-Oz, and Storyboards. Human designers create initial prototypes and guide selection; the AI designer enhances aesthetic and visual aspects (and may generate code or CAD in support of prototypes).

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2.1. Discover

In the Discover phase, designers focus on three key methods: Personas, Scenarios, and Affinity Analysis. Personas and Scenarios provide an understanding of user experiences when interacting with a product, service, or system. Human designers create the relevant personas, while AI designers assist in generating scenarios based on persona profiles.

For Affinity Analysis, human designers extract user needs from the generated scenarios and cluster the needs into categories, either manually or using AI (Figure 4).

Figure 5 illustrates two types of devices used for design tasks within Miro: laptops and Microsoft Surface Hubs. Workshop participants collaborate as teams to develop design outputs under the guidance of a facilitator, who supports each team to ensure cohesion and structured progress.

2.2. Define

In the Define phase, participants apply Activity Diagrams, System Functions, and Hierarchy of Purpose to systematically structure and refine design opportunities. In the Activity Diagram method, human designers map sequences of user interactions with the product, service, or system, providing a structured representation of key activities. The System Functions method then involves defining and categorizing the functional requirements of the intended design solution, ensuring alignment with user needs and design objectives. Finally, the Hierarchy of Purpose method supports the reframing of the original opportunity statement by abstracting it into broader opportunity statements, allowing for a more strategic exploration of design directions. At this stage, AI is introduced to refine and generate more specific opportunity statements based on an initial HMW to support the Hierarchy of Purpose method. Before progressing to the Develop phase, human designers select one or two refined opportunity statements to serve as the foundation for ideation. An example of the Hierarchy of Purpose template used in the design innovation workshop is presented in Figure 6.

2.3. Develop

In the Develop phase, the methods applied for ideation are Mind Mapping, C-Sketch, and Real-Win-Worth. Mind Mapping enables human designers to generate a diverse set of ideas by structuring text-based concept descriptions in a hierarchical tree, which are then expanded with the assistance of AI (in the AI-enhanced workflow) to introduce additional variations and explore alternative directions. C-Sketch is a collaborative sketching technique in which each participant draws three ideas on a sheet of paper before passing it to a teammate. Each participant then iterates on the sketches, adding new ideas or modifying ideas already on the page, before passing the sheet again at timed intervals until the sheets return to the original participants. C-Sketch leverages group efficiency by having each team member actively contribute in parallel. Real-Win-Worth is a structured decision-making method that allows designers to systematically evaluate and filter ideas based on three key criteria: Win (desirability), Worth (viability), and Real (feasibility). RWW provides systematic filtering through sequential elimination and facilitates a smooth, rapid selection process that is suitable for

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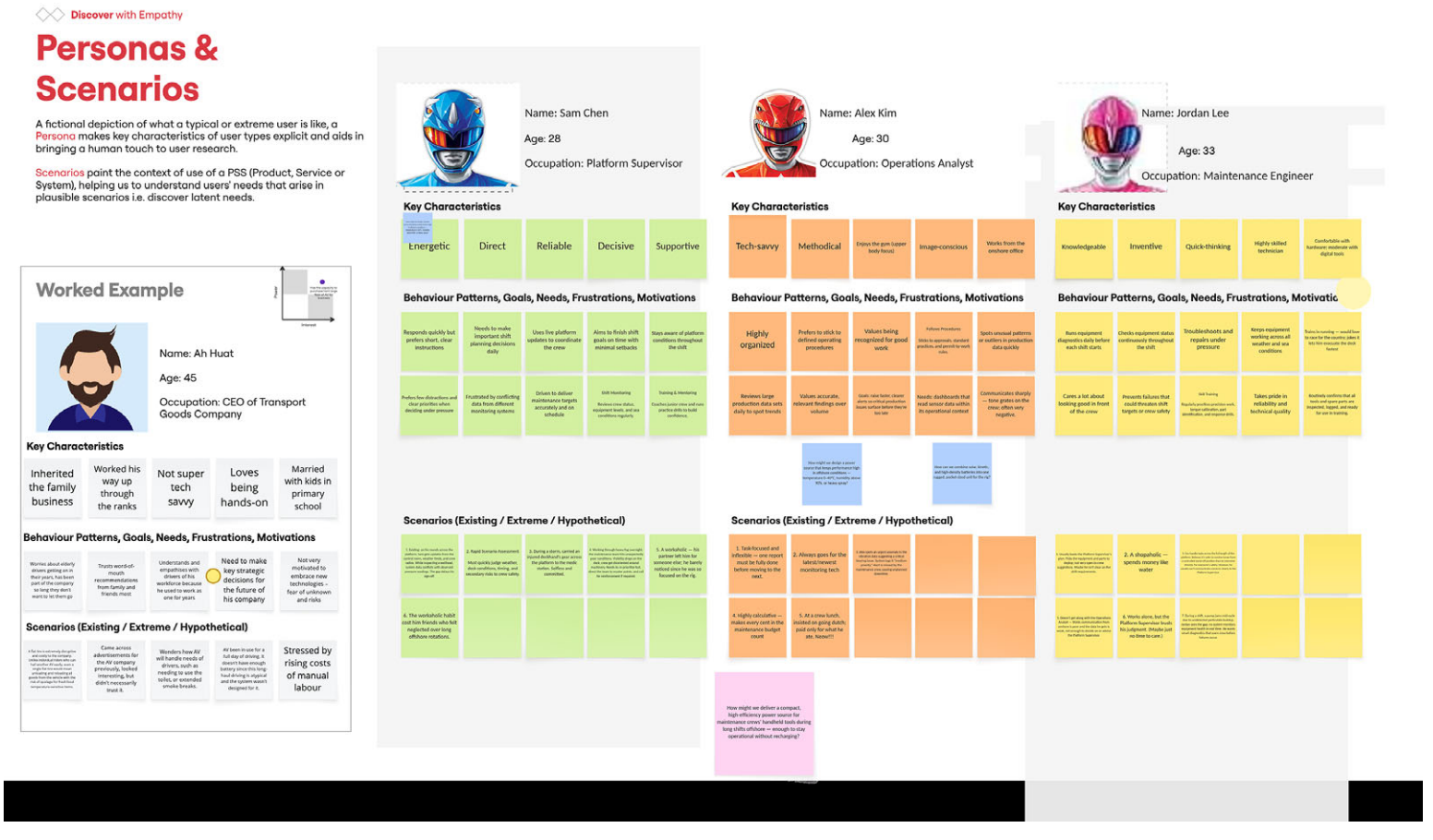


Figure 4. An example of the Personas & Scenarios template used in design innovation workshops, implemented on a Miro board (a digital collaboration platform).

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Figure 5. The facilitator (far left) coaching the design team on completing their design tasks in a workshop.

evaluating large ideation sets. By applying this approach, designers identify the most promising concepts to advance into the Deliver phase.

An example of the Mind Mapping template used in the design innovation workshop is presented in Figure 7.

2.4. Deliver

In the Deliver phase, human designers engage in rapid paper prototyping, culminating in a pitching exercise which is typically attended by senior stakeholders in their organization to secure buy-in and seed future projects. Methods applied in this section are storyboarding, paper prototyping, and pitching. In storyboarding, participants craft a sequence of images depicting usage of the proposed solution; while in paper prototyping, the form is rapidly expressed using basic crafting materials to support a live-action demonstration, which is not functional but serves to demonstrate the concept. AI can support this process by providing high-fidelity images for storyboards, as well as rapid mock-ups of user interfaces or detailed renderings of design concepts to support the pitch exercise (prototypes of UI interfaces or other software may be partially functional through AI-accelerated workflows).

An example of one of the prototyping methods, the Storyboarding template, used in the design innovation workshop is presented in Figure 8.

In each workshop, participants are encouraged to deliver an engaging and interactive pitch to a panel consisting of the design trainer, design facilitators, fellow participants and senior stakeholders from their organization (when possible). This presentation involves demonstrating the developed prototypes and articulating the proposed solutions' value and feasibility. To foster engagement and

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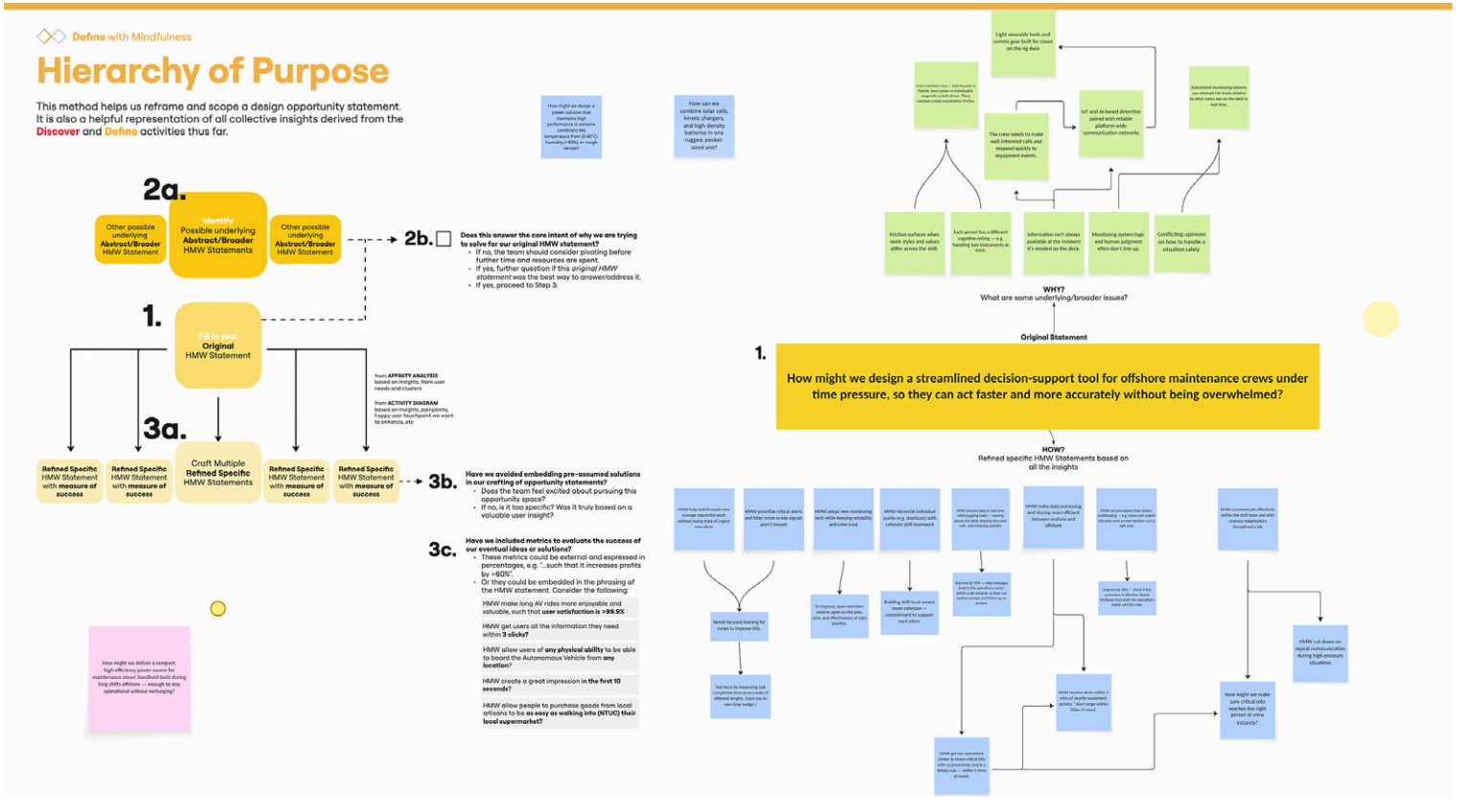


Figure 6. Template for the Hierarchy of Purpose method done in a Miro board. Participants abstract their problem statement into more generalized ("why," green in this sample) or more specific problem statements ("how," blue in the sample) in order to develop a more actionable and impactful problem statement. AI use in this step is generally limited to ensure contextual alignment is driven by empathy.

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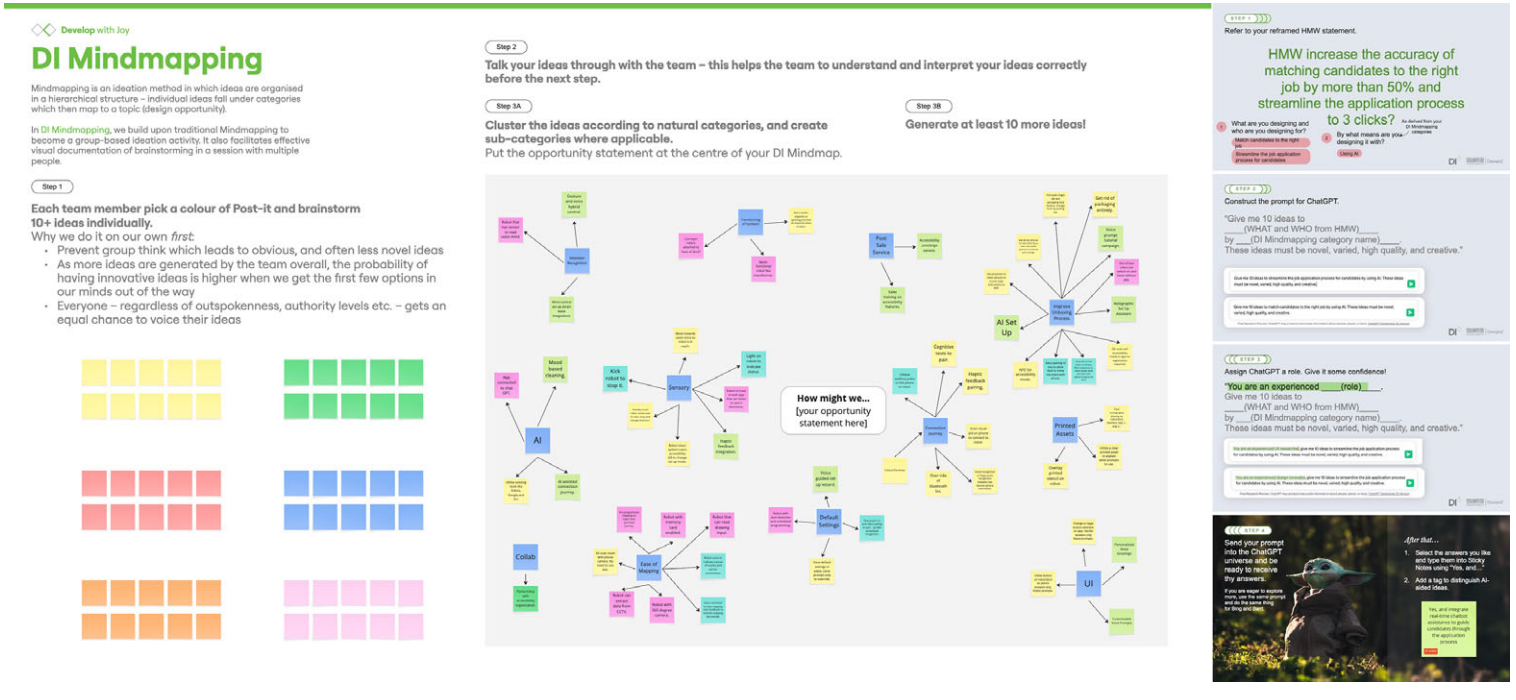


Figure 7. Template for the Mind Mapping method done in a Miro board. Here, each participant chooses a colour of post-its to track their ideas; these are clustered in the traditional manner, and in the AI-augmented workflow participants use foundation models to generate additional ideas after a first round of human-led ideation.

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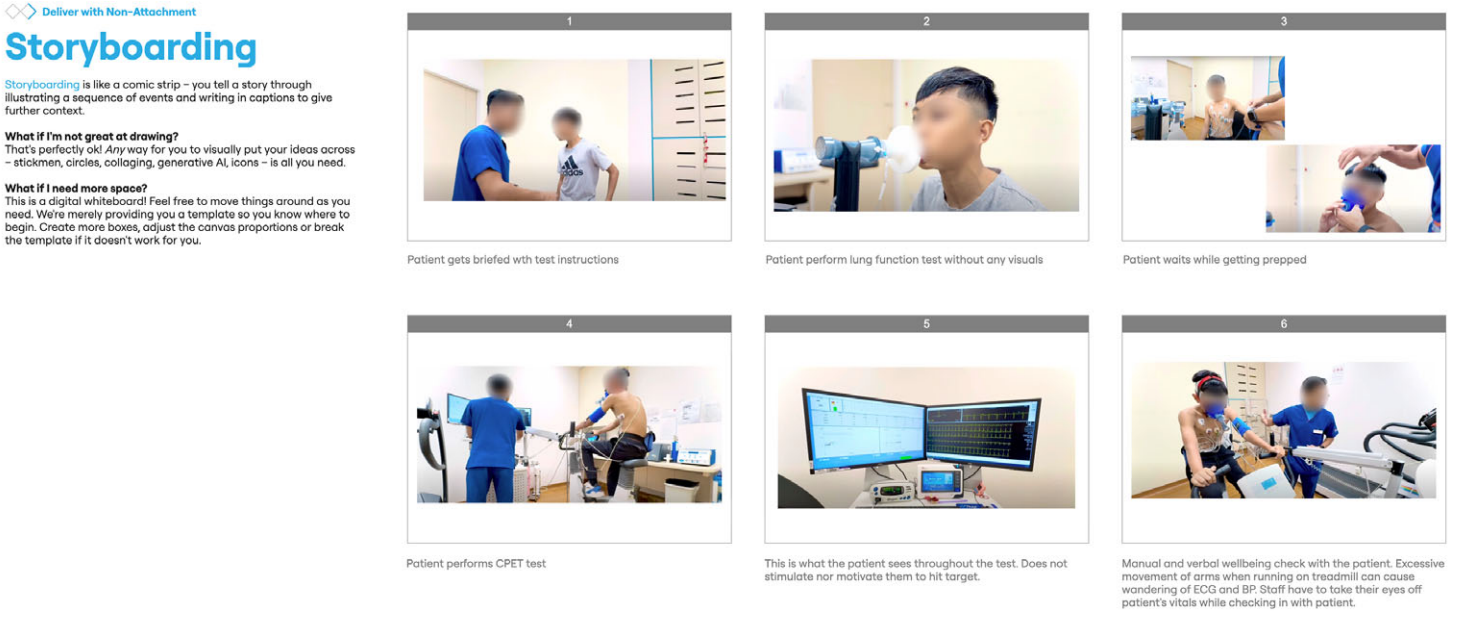


Figure 8. Template for the Storyboarding method done in a Miro board. Participants prepare content through web search, drawing, or AI generation to populate the storyboard sequence.

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recognize exceptional work, a mini competition is typically held at the conclusion of the workshop, where all participants vote on the most compelling pitch and the winning team receives an award.

3. Research methodology

This section presents the overall research methodology applied in the study, as shown in Figure 9. Participants engaged in one of two workshop formats, either human-only or AI-augmented. We first directly compare the quality of the results from individual methods generated by humans in the traditional, human-only workflow against results using an AI tool. This allows direct comparison with metrics using identical problem statements. Second, we evaluated the participant preference for the AI-augmented workshop format versus the baseline workshop format. It should be noted that while ChatGPT 3.5 was used in generating synthetic data for direct comparison to the human-only workshop flow, participants in the augmented workshop flow are encouraged to apply a variety of AI tools at the end of each method to enhance results and streamline their workflows, thus enabling the proposed approach to remain relevant as AI tools rapidly evolve. The qualitative comparison investigates the overall perception of an end-to-end AI-augmented workflow. The direct comparisons are designed to evaluate whether replacing certain steps of the design process with AI augmentation is associated with any reduction of quality of those steps; the comparison is intended to check that AI augmentation does not degrade the quality of individual steps; it is illustrative and boundary-setting rather than a controlled performance test.

3.1. Prompting strategy for AI-driven design tasks

Prompts for ChatGPT 3.5 were crafted to parallel typical design workshop instructions and problem statements, maintaining consistency in task framing and language while allowing the natural variation inherent to real design communication. This approach follows the prompting guidelines provided in the workshop for AI-augmented methods and prioritizes ecological validity, acknowledging that minor differences in prompt phrasing or output fidelity are characteristic of authentic design practice – while AI tools continually advance in practice the

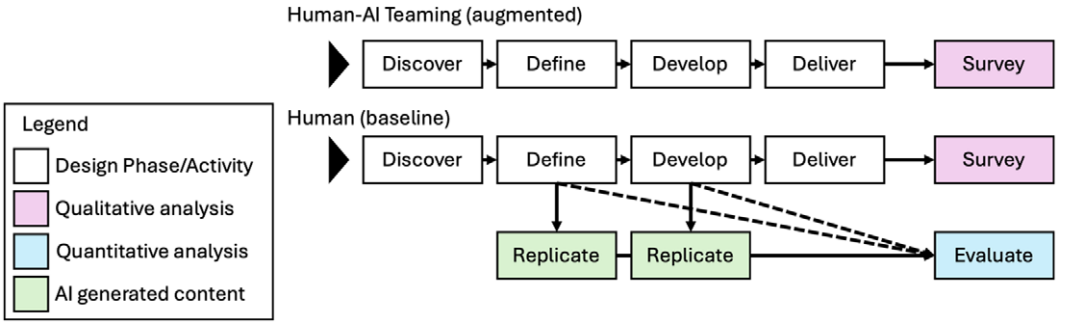


Figure 9. Research and data collection strategy.

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objective is to evaluate integration into the workflow and using tools available at the time of the study.

Both ideation and clustering tasks were conducted through ChatGPT 3.5. For clustering, GPT was prompted to group user need statements by semantic similarity, mirroring the logic of human affinity diagramming to ensure that both conditions followed comparable synthesis workflows. As AI baseline models and refined design tools continue to evolve, this study represents a snapshot of capability at the time of investigation rather than an exhaustive analysis of prompt engineering or verbosity effects. The focus is on demonstrating whether AI-augmented steps can produce outputs of comparable quality to human-only teams within an authentic workshop workflow.

Example prompts used during the replication exercise included the following:
Clustering:

- *Can you help me cluster these statements by semantic similarity: User need 1; User need 2; User need; …*

Ideation (30 ideas total, 10 per prompt):

[1] *Give 10 ideas that are novel, varied, high quality, and creative + [reframed opportunity statement].*
[2] *Give 10 ideas that are wild and imaginative + [reframed opportunity statement].*
[3] *It is the year 2080 – list 10 crazy and inventive ideas based on new technologies, lifestyles, and discoveries in the future + [reframed opportunity statement].*

3.2. Participants and data collection

Data for this study were collected from past design innovation workshops done with local professional organisations; these were workshops where the AI enhancement methods had not yet been introduced. Each team consisted of 5–6 members. Participants were industry professionals from varied backgrounds, including design engineering, systems engineering, architecture, management, and operations, with experience typically ranging from 3–15 years in their respective fields. The teams were self-formed and addressed real problems faced by their respective organizations over the course of a three-day workshop. For the direct comparison of single-method results (AI vs. Human), data sets analysed included the results of Affinity Analysis and Mind-Mapping as representative samples of two activity types: organization (synthesis) and expansion (ideation).

This experimental design allowed for a direct one-to-one comparison of human versus AI-generated results. In the AI-augmented workshops, humans will first generate results, and then refine them using AI, replacing certain steps in the design process as outlined above. Our objective here was to examine, within the constraints of a practice-based setting, whether AI-augmented steps remained of comparable quality to human-only steps; we do not treat this as a fully controlled comparison. We also report on user feedback for the integrated AI-augmented design workshops at the end of this experimental evaluation section. Direct comparison of results between AI- and non-AI-augmented workshops was deemed less suitable owing to the large amount of variations in problem statements. Some are more abstract, others less abstract, making direct comparison difficult. Therefore, we directly replicate AI-generated results for the exact problem statement addressed by each human team and compare these.

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For the Affinity Analysis dataset, for AI data generation, we used ChatGPT 3.5 to cluster the user needs extracted from each of the human team's collaboration boards. This clustering was performed for each team, resulting in an equal number of AI-augmented cluster datasets.

For the mind-mapping dataset, for AI data generation, we used the same Reframed Opportunity Statement as each human team as a prompt in ChatGPT 3.5 to generate ideas for each prompt that the human teams used. We asked ChatGPT to generate the same number of ideas as the human teams, and then categorise those ideas to form a mind map. This process resulted in an AI-generated dataset for mind mapping, each mapping one-to-one with the 20 human teams' data.

3.3. Metric selection

With numerous creativity metrics established in design research, such as novelty, feasibility, and user-centred impact, the present study focused on a targeted set of evaluation criteria aligned with the methods under examination. The metrics of Accuracy, Insightfulness, Quality, and Desirability were selected to reflect the specific nature of the synthesis and ideation tasks. This deliberate focus enables a clear assessment of method-level performance and provides a foundation for incorporating broader creativity metrics in subsequent investigations.

3.4. Data analysis methods

The performance metrics of Affinity Analysis are Accuracy of the user need clusters and Insightfulness of the user need clusters. Herein, we define accuracy as "degree to which a need is in the correct cluster," and insightfulness as "degree to which the inclusion of a need in a cluster adds meaningfully to understanding the user." The performance metrics of Mind Mapping are Quality of the ideas and Desirability of the ideas. Where quality and desirability follow typical definitions "degree to which the solution is well-formed and potentially useful," "degree to which the solution addresses user needs effectively." Two independent designers evaluated each design method using their respective assessment metrics, and inter-rater agreement was computed using Cohen's Kappa correlation technique. The AI-generated content was produced separately by the research team, while the evaluators were experienced design practitioners who did not participate in generating either the AI or human workshop outputs. To ensure impartiality, the raters were blinded to the source condition (human-only or AI-generated) before performing the evaluations. For Affinity Analysis, inter-rater agreement values were 0.645 for Accuracy and 0.634 for Insightfulness. For Mind Mapping, agreement values were 0.658 for Quality and 0.638 for Desirability. These fall within the range of moderate to substantial agreement. Following the blind evaluation, the raters jointly reviewed and resolved any discrepancies to establish the final consensus scores used for analysis. The coding scheme for Accuracy of the user need clusters in Affinity Analysis is given in Appendix.

3.5. Accuracy rating description

To evaluate the Accuracy, each reviewer determined a rating for 259 clusters of user needs (clusters-by-human and clusters-by-AI) where each cluster contains at least

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1 user need. There are 152 clusters-by-human and 107 clusters-by-AI. The metric scale for the Accuracy rating is given in Appendix.

We confirm that each need is valid and fits the category into which it was assigned using the following logic sequence:

1. What does a "valid user need" mean? A valid user need contains a requirement/need/desire of a user that ought to be addressed. It does not contain a solution, function, or a scenario.
2. What does a "user need that fits the cluster name" mean? A user need that fits the cluster name means this user need aligns with the cluster name that is being represented/defined.

3.6. Insightfulness rating description

To evaluate the Insightfulness, each reviewer determined a rating for the same 259 clusters of user needs (clusters-by-human and clusters-by-AI) as in the Accuracy rating, where each cluster contains at least 1 user need. There are 152 clusters-by-human and 107 clusters-by-AI. The metric scale for the Insightfulness rating is given in Appendix.

We also consider whether the inclusion of a user need in a given cluster is insightful as follows:

1. What does a "user need is insightful" mean? A user need is insightful when it is useful, and there are some surprising/non-obvious elements being observed. It answers the question of "Would you have thought of this new perspective if the user need is not mentioned?"

An example of Insightfulness ratings applied to a small subset of the ideas is given in Appendix.

3.7. Quality rating description

To evaluate the Quality, each reviewer determined a rating for 1,779 ideas (ideas-by-human and ideas-by-AI). There are 152 ideas-by-human and 107 ideas-by-AI. The metric scale for the Quality rating is given in the table below. The rubric to rate the Quality of the ideas in Mind Mapping is given in Appendix.

3.8. Desirability rating description

To evaluate the Desirability, each reviewer determined a rating for the same 1,779 ideas (ideas-by-human and ideas-by-AI) as in the Quality rating. There are 1,089 ideas-by-human and 690 ideas-by-AI. The metric scale for the Desirability rating is given in the table below. The rubric applied to rate the Desirability of the ideas in Mind Mapping is given in Appendix.

4. Results

Overall ratings are accumulated and summarized into a table (Appendix). The table below shows the averages of the 20 selected Opportunity Statements from the 20 teams in the human-only condition. These data sets were evaluated for the metrics of Affinity Analysis (Accuracy and Insightfulness) and Mind Mapping

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(Quality and Desirability). The columns "Human" and "AI" mean that the respective metrics have their outputs done by humans and AI separately. For clarity, the same team–problem statement pairing was applied consistently across statements 2–20. For statement 1, one team's Mind Mapping data were unavailable, and an additional team dataset was substituted to maintain a complete set of 20 samples. As this study draws from practice-based workshops rather than laboratory conditions, some variance in experimental parameters is expected.

4.1. Accuracy and insightfulness overall average

Next, we report the overall average of the Accuracy and the Insightfulness metrics across all the Opportunity Statements separated by Human and AI (Table 2).

The results for Accuracy and Insightfulness averaged over all Opportunity Statements/groups are then calculated using a t-test. With a paired t-test done for the Accuracy results, the p-value is 0.0092, which is less than 0.05. This indicates that the result is statistically significant. With a paired t-test done for the Insightfulness results, the p-value is 0.8259, which is more than 0.05. Since the twentieth Opportunity Statement has no Insightfulness average in clusters-by-human, we only did the t-test for the first 19 Opportunity Statements. This indicates that there is no statistical difference in the results.

4.2. Quality and desirability overall average

Table 3 states the overall average of the Quality and the Desirability metrics across all the Opportunity Statements separated by Human and AI.

The results for Quality and Desirability averaged over all Opportunity Statements/groups are then calculated using a t-test. With a paired t-test done for the Quality results, the p-value is less than 0.0001. This indicates that the result is statistically significant. With a paired t-test done for the Desirability results, the p-value is less than 0.0001, indicating a statistically significant difference on this metric.

AI-augmented ideas scored higher on these metrics on average. We interpret this cautiously: as discussed below, these scores could be confounded by output

Table 2. Overall average between human and AI (affinity clustering)

	Accuracy	Insightfulness
Human	3.83	2.4
AI	4.22	2.41

Table 3. Overall average between human and AI (ideation)

	Quality	Desirability
Human	2.59	3.1
AI	4.75	4.42

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verbosity and study-specific rubrics, so we read them as evidence that AI augmentation did not reduce quality, rather than as evidence of intrinsic superiority.

4.3. General feedback from participants

This section reports participants' self-reported perceptions of the AI-augmented workflow; it characterises overall preference and satisfaction rather than a fine-grained analysis of how participants engaged with AI at each step. Data were gathered using short surveys administered at the end of each workshop day to capture evolving perceptions of engagement, relevance, and learning across the multi-day sessions. The survey instrument consisted of Likert-scale and numerical rating questions designed to measure participant engagement, perceived relevance, clarity of delivery, and confidence in applying the introduced methods. The surveys included questions such as "I found the workshop engaging," "The methods covered are relevant to my work," and "I feel confident applying these methods."

Results presented here represent the aggregated averages across all survey questions and all participants. Data include end-of-day responses from each day of the workshops (Day 1, Day 2 and Day 3) and from both experimental conditions – the human-only and AI-augmented workshops. Because the question phrasing and number of items varied slightly between workshop instances, aggregate scores were computed to enable cross-comparison. All ratings were converted to a standardized 1–10 scale, where 10 represented the highest level of agreement or

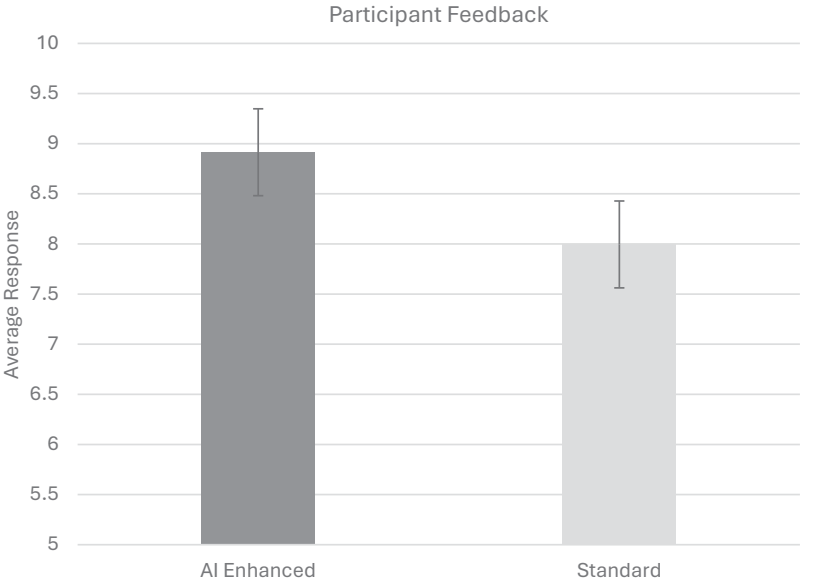


Figure 10. Aggregated participant feedback on overall workshop experience (a) and applied methods (b), comparing pre- and post-incorporation of AI-ideation methods. Results represent total averages across all survey questions and end-of-day evaluations (Days 1, 2 and 3) for both workshop formats. Data are averaged across multiple human-only and AI-augmented workshops conducted between 2022 and 2024. Plus or minus one standard deviation shown: 0.43 and 0.46, respectively.

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satisfaction. This approach ensured consistency in evaluating both the AI-enhanced design methods and the overall workshop experience across different participant groups.

Overall, participants found the workshops informative and rated the AI-enhanced methods highly. The average score for the evaluation of specific AI-augmented methods was *8.54/10*, while overall workshop feedback indicated that the majority of participants *strongly agreed* that the topics were relevant, well delivered, and applicable to their own professional practice (Figure 10). Collectively, they demonstrate a consistent positive response toward AI integration in design workflows and indicate that participants reported strong engagement and perceived value in the AI-augmented sessions; these are self-reported perceptions rather than measured learning outcomes.

5. Discussion

Examination of the method-level results indicates that AI-augmented steps performed comparably to human teams in Affinity Analysis (synthesis) and Mind Mapping (ideation), within a semi-controlled, practice-based setting. However, these findings must be interpreted with caution, as multiple factors influence the comparative performance of human- and AI-generated outputs.

For Affinity Analysis, AI-generated clusters scored modestly higher in accuracy. This is consistent with AI supporting structural organisation of user needs; note that in this task AI only organised human-generated content and produced none of its own. However, in terms of insightfulness, AI-generated clusters scored equivalently to human-generated clusters. It should be noted that this reflects that AI performed well in terms of generating clusters that meaningfully capture similarity between ideas. Note that in the Affinity mapping task, AI did not generate any content, but rather simply organised needs generated by the team.

For Mind Mapping, AI-augmented ideas scored higher on the quality and desirability metrics (by 83% and 42% on these rubrics); however, these differences may be substantially attributable to verbosity and rubric design and should not be read as a clear performance advantage. It may be noted that AI-generated ideas demonstrated a greater level of detail, which may have potentially influenced apparent quality, while humans often reported more shorthand and brief descriptions. While detail is important to accurately portray an idea, there may also be some value to ambiguity, and this topic should be explored further in future work. However, this result is consistent with AI being useful in generative tasks, while remaining subject to the confounds noted above.

Given that such results are generated in a matter of seconds, while the same process may take several hours for a human team, there is a clear opportunity to apply AI during design to expand and refine the initial insights generated by human teams.

These results are broadly consistent with contemporary studies reporting that AI can contribute usable design outputs. Furthermore, they extend the evaluation of AI in design to an integrated, end-to-end design innovation context, where participants responded positively and found the workshops more engaging and effective when the process incorporated integrated AI support.

We observe that AI impacts design through several paradigm shifts: it offers the ability to synthesize user data, generate images for persona or scenario

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visualization, expand the design concept search space, rapidly produce code or UI prototypes, and facilitate generating and evaluating bills of materials. In short, AI enables designers to rapidly explore the design space, automating and augmenting research in much the same way that search engines revolutionized data retrieval, but across more stages and more processes within the design workflow.

However, a number of studies have identified cognitive offloading as a concern. Anecdotally, we observe that in cases of rush, or with individuals new to design, they may over-rely on AI-generated results, and while AI-supported idea generation is productive, it may lack the nuance or contextual relevance of human-generated content when applied to real-world problems. This underscores the critical role of the human as navigator, closely integrated within the process, as well as the importance of leading with human-generated ideas to mitigate fixation. As established in prior work, once exposed to existing ideas, designers are cognitively predisposed to anchor on them, conserving the activation energy otherwise required to generate novel alternatives. Care should therefore be taken to critically evaluate AI outputs and push beyond initial generative results. Future work should explore the pacing of this human–AI dialogue, conduct integrative reviews of the long-term cognitive impacts of AI on design, and develop step-by-step best practices for AI integration – recognizing that these will continue to evolve alongside the tools themselves.

To this end, the approach presented offers an illustrative, practice-based reference for how AI can be integrated across a full design workflow, providing an example structure for human–AI teaming throughout the design process. By mapping out an explicit template for the human–AI dialogue, specifying an example flow for where human input leads and where AI augments, a clear expectation is established. This is particularly geared to support educational and early-stage (novice) practice settings, establishing that the end-to-end design process is not intended to be fully automated. The template serves as a scaffold to facilitate preserving human agency, critical for meaningful outcomes, at each phase while making the potential to leverage AI contributions deliberate.

6. Limitations and future work

While this study provides empirical comparisons between human and AI-augmented design methodologies, the experimental approach is semi-controlled, introducing several limitations. Conducting design workshops with practicing professionals offers valuable ground-truth data on how AI may be perceived and integrated into real-world design processes. However, this approach also introduces variability that limits strict control over experimental conditions.

First, participant variability may influence the results, as differences in professional backgrounds, expertise levels, and problem-solving approaches could contribute to variations in human-generated outputs. Second, problem statement variability across different workshops introduces another layer of complexity, as certain design challenges may be inherently more suited to AI augmentation than others. To mitigate this, comparisons were conducted using the same problem statements from the human-only workshops, with AI-generated sample content produced on a matched team-by-team basis. Third, the time span of the workshops presents additional external factors, including differences in facilitation styles and potential iterative learning effects across participants.

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As the present study focused primarily on text-based content to enable quantitative comparison across methods, future work should extend this approach to include visual and multimodal design activities – particularly those that alternate dynamically between sketches, diagrams, and models. Future investigations could include: (1) evaluation of sketch-based and visual design content; (2) incorporation of multimodal inputs such as text, image, and 3D geometry; and (3) exploration of combinatorial or adaptive AI workflows that dynamically reconfigure based on user interaction.

Finally, this study was intentionally scoped as an initial examination of process-level integration between human and AI design activities rather than a controlled evaluation of prompt engineering, verbosity effects, or model optimization. Such variables will continue to evolve as AI systems advance; therefore, efforts to control them rigidly would risk obscuring the practical realities of contemporary design workflows. The present approach instead reflects how AI can be naturally integrated within authentic design practice, offering a foundation for future controlled studies to build upon. Relatedly, while the survey captures participant preference and self-reported experience, a fine-grained qualitative analysis of how participants engaged with AI across individual workflow steps is beyond the scope of this practice-based study; we identify this as a direction for future work.

7. Conclusions

As AI tools continue to evolve rapidly, with a growing body of research demonstrating performance comparable to human designers across a range of tasks, there is a need to examine how established design process approaches, such as the Triple Diamond, should adapt to accommodate human–AI collaboration. This study explored a dialogue-based strategy in which participants alternate between human-driven and AI-driven activities across the end-to-end design process. Importantly, the proposed approach is agnostic to both specific design methods and AI tools, allowing it to remain applicable as methods and models continue to advance. The approach and workshop templates are provided in detail, and the analysis indicates positive participant reception.

Participants showed a clear preference for the AI-augmented workshop format over the human-only version. Industry professionals described the AI-augmented sessions as more engaging and efficient, particularly in maintaining progress during ideation. This preference is supported by the quantitative comparisons, which indicate that AI-augmented outputs in both methods were of comparable quality, structurally coherent, and produced rapidly; we do not claim a performance advantage given the noted confounds.

The workshops involved participants with three to 15 years of experience in engineering, systems, product development, or operations fields. While they were familiar with applied engineering and design practice, most were relatively new to structured design innovation methods. The AI-augmented approach appeared to make these methods more approachable and practical, leading to strong participant engagement and continued interest in future AI-augmented workshops. This trend suggests that AI is increasingly viewed not as a disruptive tool or "at odds" with the human designer, but as a natural extension of the design process.

Overall, the findings indicate that AI-augmented co-design can support a positive experience of design activities. Further, the method-level results indicate

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that such augmentation did not degrade quality in the sampled methods. Together, these observations point toward the growing role of AI as an enabling and integrative element in future design innovation practice.

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Appendix: Metrics applied in quantitative analysis

Table A1. Accuracy coding scheme with the procedures clearly explained

No	Step to rate accuracy of clustered needs
1	Understand the opportunity statement with the personas and scenarios
2	Go to the first cluster
3	Understand the cluster and its user needs
4	Count how many user needs are both a valid user need and fit the cluster name
5	Calculate the score of the cluster using the *Accuracy Score Formula*
6	Based on the score, rate the accuracy of the cluster on a scale of 1–5
7	Go to the next cluster
8	Repeat steps no. 3–7 until rating has been done for all clusters

Table A2. Definitions applied to the Accuracy rating with a scale of 1–5 based on the Accuracy Score generated

Rating	Not accurate (1)	Less accurate (2)	Moderately accurate (3)	Very accurate (4)	Extremely accurate (5)
Definition	The cluster minimally addresses the identified user needs.	The cluster partially aligns with some user needs but lacks depth or comprehensiveness.	The cluster somewhat reflects user needs, but there is room for improvement.	The cluster largely aligns with identified user needs, covering most essential aspects.	The cluster comprehensively addresses all identified user needs with precision.
Score	0–0.2	0.21–0.4	0.41–0.6	0.61–0.8	0.81–1

Accuracy Score = $\frac{a}{n}$, where

a = no. of user needs that fit the cluster name.
n = total no. of user needs in the cluster.

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Table A3. A worksheet for rating the Accuracy extracted from a small subset of the dataset

	Human clusters			
Cluster name	No. of user needs	No. of user needs that fit the cluster	Score	Rating
Winning a challenge	1	0	0	1
Work efficiency	13	7	0.54	3
Cybersecurity	7	6	0.86	5
Communication	3	2	0.67	4
Collaboration	7	3	0.43	3
Personal space	2	0	0	1
Happiness	5	0	0	1

The coding scheme to rate the Insightfulness of the user need clusters in Affinity Analysis is as follows (Table A4):

Table A4. Insightfulness coding scheme with the procedures clearly explained

No	Steps to rate insightfulness of clustered user needs
1	Out of all the clusters with an accuracy rating of 3 and above, proceed to rate its insightfulness, and we call this as "accurate cluster"
2	Understand the opportunity statement with the personas and scenarios
3	Go to the first accurate cluster
4	Understand the accurate cluster and its user needs
5	Determine whether each user need is insightful
6	Count how many user needs are insightful
7	Calculate the score of the cluster using the *Insightfulness Score Formula*
8	Based on the score, rate the insightfulness of the cluster from a scale of 1–5
9	Go to the next accurate cluster
10	Repeat steps no. 4–9 until rating has been done for all clusters

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Table A5. Definitions applied to the Insightfulness rating with a scale of 1–5 based on the Insightfulness Score generated

Rating	Not insightful (1)	Less insightful (2)	Moderately insightful (3)	Very insightful (4)	Extremely insightful (5)
Definition	The cluster lacks depth and fails to provide meaningful understanding or direction. It may be overly simplistic, obvious, or unrelated to the problem at hand. There's little value in these needs for guiding product development or decision-making.	The cluster offers some insights into user preferences or pain points, but it lacks specificity or clarity. While it may point towards potential areas for improvement, it does not provide sufficient detail or context to inform actionable solutions effectively.	The cluster offers valuable insights into user behaviours, motivations, and pain points. It provides a solid foundation for understanding user requirements and shaping product development efforts. However, there may still be room for further exploration and refinement to uncover deeper insights.	The cluster offers rich and detailed insights into user preferences, goals, and challenges. It provides clear direction for product development and decision-making, highlighting key areas of opportunity for addressing user needs effectively. These insights are likely to drive meaningful innovation and differentiation in the product or service.	The cluster represents a comprehensive understanding of user behaviours, motivations, and pain points. It offers deep insights into the user experience, enabling precise targeting of user needs and preferences. These insights are invaluable for guiding product strategy and development, leading to highly impactful and user-centric solutions.
Score	0–0.2	0.21–0.4	0.41–0.6	0.61–0.8	0.81–1

$$\text{Insightfulness Score} = \frac{b}{n}, \text{ where}$$

b = no. of user needs that have one or more insights.
n = total no. of user needs in the cluster.

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Table A6. A worksheet for rating the Insightfulness extracted from a small subset of the dataset

	Human clusters			
Cluster name	No. of user needs	No. of user needs that have one or more insights	Score	Rating
Winning a challenge	1			
Work efficiency	13	6	0.46	3
Cybersecurity	7	2	0.29	2
Communication	3	1	0.33	2
Collaboration	7	1	0.14	1
Personal space	2			
Happiness	5			

Table A7. Definitions applied to quality rating with a scale of 1–5

Rating/score	1	2	3	4	5
Definition	The idea written is abstract/unclear; it does not say "what," it does not describe how the idea works or its advantages to the users.	The idea written is understandable; it says about the "what," it does briefly explain what the idea is for, but it does not describe how the idea works or its advantages to the users.	The idea written is understandable; it says about the "what," it does briefly explain what the idea is for; it implicitly describes how the idea works and/or its advantages to the users.	The idea written is comprehensive; it says about the "what," it thoroughly explains what the idea is for; it incompletely describes how the idea works, but it mentions its advantages to the users.	The idea written is comprehensive; it says about the "what," it thoroughly explains what the idea is for, it fully describes how the idea works, and its advantages to the users.

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Table A8. Definitions applied to desirability rating with a scale of 1–5

Rating/score	1	2	3	4	5
Definition	The idea is not relevant to the opportunity statement/user needs as it does not solve any problem, and it cannot motivate the users.	The idea is slightly relevant to the opportunity statement/user needs, but it only solves some parts of the problem, and it can slightly motivate the users.	The idea is more relevant to the opportunity statement/ user needs, but it only solves some parts of the problem, and it can fairly motivate the users.	The idea is more relevant to the opportunity statement/user needs; it almost fully solves the problem, and it can moderately motivate the users.	The idea is most relevant to the opportunity statement/user needs, it fully solves the problem, and it can highly motivate the users.

Table A9. Average scores between human and AI

	Accuracy		Insightfulness		Quality		Desirability	
Statement	Human	AI	Human	AI	Human	AI	Human	AI
1 (Affinity)	4.29	4.2	2.17	3.5				
1 (Mind map)					3.65	4.67	3.57	3.47
2	4.6	5	4.6	4.33	2.94	4.7	3.29	4.47
3	4.33	5	3.33	2.86	2.85	4.8	3.33	4.4
4	4.33	4.38	2.73	2.88	2.27	4.37	2.62	4.4
5	4.33	4.33	2.17	2.6	3.26	4.63	3.26	4.4
6	3.67	4.17	2.11	1.17	2.66	4.9	3.02	4.33
7	3.8	3.5	3.25	2.33	2.95	4.67	3.16	4.47
8	3.33	4.6	1.4	1.4	1.63	4.67	2.76	4.27
9	4.2	4.75	2.6	2.25	2.52	4.97	3.12	4.83
10	3.9	4.4	2.56	3.2	2.49	5	3.08	4.13
11	4.2	3.8	3	2.6	2.19	4.7	2.97	4.27
12	3	3.25	1	1	1.94	4.63	2.91	4.2
13	4.5	4.67	2.13	1.5	2.7	4.47	3.27	4.2
14	4.25	4.4	3	3	2.53	4.63	2.91	4.47
15	2	2	1	2	1.96	5	2.61	4.87
16	4.44	4.91	1.78	2	3.13	4.53	3.1	4.4
17	4	4.25	2	1.5	2.47	4.97	3.2	4.87
18	3.6	4	2.75	3.25	2.28	5	2.7	4.77
19	4.5	5	2	1.6	2.48	4.87	3.02	4.5
20	1.4	3.75	–	3.33	2.83	4.8	3.33	4.7

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