academic quarter
akademisk kvarter
research from the humanities
AAU

Fostering creativity and self-efficacy through collaborative learning using generative Artificial Intelligence (AI) in the product design visualization process

Muhammad Jameel Mohamed Kamil *Senior Lecturer in Industrial Design at the Faculty of Applied and Creative Arts, Universiti Malaysia Sarawak (UNIMAS). His research focuses on medical product design, design science, 3D technology, indigenous arts and cultural heritage, and User-Centred Design (UCD).*

Amirul Fahmi Razali *Senior Lecturer in Industrial Design at Universiti Sultan Zainal Abidin. His research focuses on design identity, culture-oriented design, material–emotion studies, and AI-assisted design. He actively leads academic–industry collaborations and design education initiatives.*

Rosalam Che Me *Senior Lecturer in Industrial Design at Universiti Putra Malaysia (UPM). A UPM alumnus with a PhD from Politecnico di Milano, his expertise spans product design, assistive technology, User-Centred Design (UCD), design for disabilities, and biocomposite product design.*

Mohd Najib Abdullah Sani *Senior Lecturer in Industrial Design at Universiti Malaysia Sarawak (UNIMAS). He is committed to teaching, research, and service in medical product design.*

Abstract
Generative models in Artificial Intelligence (AI) are increasingly employed across diverse fields, including product design, for tasks like shape recognition and design creation. This trend underscores generative models' ability to bridge offline and online environments in creative endeavors. The article investigates the potential of

integrating generative image AI into visualization process among product design students. Using image-based research analysis and semi-structured interviews, this study involved 50 product design students as respondents. The findings highlight that integrating generative AI tools, particularly the ChatGPT 4.0, significantly improves students' creativity and self-efficacy through collaborative learning, and streamlines the design process. The findings also close the gap between creative concepts and practical applications, and offers a robust framework for evaluating AI-generated content. The contribution of the study underscores the transformative potential of generative AI tools in product design education, showcasing the effectiveness in fostering creativity, efficiency, and design quality through collaborative learning.

Keywords: Artificial Intelligence; Product Design; Creativity; Self-Efficacy; Collaborative Learning

Introduction

Generative Artificial Intelligence (AI) has transformed content creation by producing realistic text, images, audio, and video through pattern learning rather than rule-based programming (Ye et al. 2024). Tools such as Stable Diffusion and DALL-E now enable high-quality visual generation from simple text prompts, lowering the need for artistic or technical skills. Likewise, large language models like GPT extend AI's role in reasoning, communication, and design-related tasks (Tian et al. 2024). Generative AI also reduces technical barriers and opens new opportunities for creative innovation (Hashmi and Bal 2023). In product design education, generative AI has the potential to reshape ideation practices. The discipline emphasizes competencies such as design thinking, user research, ergonomics, prototyping, and user experience (Huang et al. 2024; Mohamed Kamil and Abdullah Sani 2021). These align with the four stages of design thinking: (1) empathy, (2) define, (3) ideation, and (4) prototyping and testing. The ideation phase is especially crucial because it encourages divergent thinking and conceptual exploration (Jonson 2005; Self, Evans, and Kim 2016; Nelson et al. 2009; Chien et al. 2022; Mohamed Kamil et al. 2024). Traditionally, ideation relies on hand-drawn or digital sketches, which may be limited by time constraints and individual drawing ability. Integrating generative AI into ideation introduces new possibilities for co-creation, allowing rapid translation of concepts into visual outputs (Huang et al. 2024). This accelerates idea exploration and supports self-efficacy as students interact with AI as a responsive partner that provides instant feedback. Crafting precise textual instructions (prompt engineering) is essential to align AI-generated visuals with design intent and ethical considerations (Short and Short 2023; Tian et al. 2024). Within collaborative learning settings, AI can function as both a creative stimulus and a pedagogical tool that connects imagination with visualization. This study examines the use of generative image-based AI in the ideation phase of product design education. It explores how AI affects students' creative outputs and self-efficacy when used within a structured collaborative environment. The research focuses on two objectives: (1) to evaluate the direct influence of generative AI on the creativity and variety of student-generated design visuals; and (2) to assess its indirect impact on self-efficacy and creative confidence through collaborative learning. These aims contribute to theoretical and pedagogical insights on integrating AI into design education to enhance creativity, collaboration, and learner confidence.

Collaborative Learning

Collaborative learning is grounded in sociocultural theory, which views knowledge as co-constructed through interaction and scaffolding within shared problem spaces (Vygotsky 1978). It involves learners working jointly to build understanding or generate solutions (Dillenbourg 1999). The cooperative learning model emphasize positive interdependence, individual accountability, and promotive interaction as essential for effective group work (Johnson and Johnson 1989). Beyond cognitive gains, collaboration supports communication, negotiation, and perspective-taking (Laal and Ghodsi 2012). In product design education, collaboration strengthens ideation, critique, and refinement, as ideas improve through collective iteration. In this study, collaborative learning extends beyond peer interaction to include engagement with digital tools, particularly generative AI which acts as a mediating artifact within a sociomaterial learning environment (O'Malley 1995). This reflects contemporary views of learning as distributed across people, tools, and representations rather than located solely in individual cognition.

Creativity

Creativity is increasingly understood as a socially embedded process rather than an isolated mental act (Csikszentmihalyi 1996). Csikszentmihalyi's Systems Model conceptualizes creativity as emerging from interactions among three elements: the person who generates ideas, the domain of symbolic knowledge, and the field that evaluates and legitimizes contributions (Csikszentmihalyi 1999). In this study, students act as the "person," generative AI as a tool for product design visualization represents the "domain," and the research team functions as the "field." Expanding this view, Glăveanu's Distributed Creativity positions creativity as enacted through human and material interactions (Glăveanu 2014; Glăveanu 2021). Generative AI operates as a creative tool that shapes ideation and influences output through co-construction. By integrating both perspectives, this study situates ideation as an emergent process involving learners, AI systems, design briefs, and evaluative practices rather than individual cognition alone.

Self-efficacy

Self-efficacy refers to individuals' beliefs in their ability to execute actions required to achieve specific outcomes (Bandura 1997). Within Bandura's Social Cognitive Theory, it influences motivation, persistence, and performance (Bandura 1986). Its development is shaped by mastery experiences, vicarious learning, social persuasion, and affective states (Bandura 1986). High self-efficacy supports resilience, risk-taking, and persistence in creative tasks (Pajares and Schunk 2002; Zimmerman 2000). In product design, students' belief in their creative capabilities affects their willingness to explore novel directions. Generative AI can strengthen self-efficacy by offering cognitive support, but may also create dependence or intimidation if perceived as superior (Tierney and Farmer 2002). Accordingly, this study positions self-efficacy as a mediating factor shaping how students engage with AI-supported ideation.

Methodology

This study is guided by a conceptual framework that integrates collaborative learning, creativity theory, and self-efficacy. Generative AI is positioned not as a technological resource but as a mediating tool and co-participant in problem-solving during the ideation phase (Vygotsky 1978; Johnson and Johnson 1989). In line with systems-based models of creativity (Csikszentmihalyi 1999; Glăveanu 2014), creative outcomes are viewed as emerging from the interaction between learners, peers, and tools. Simultaneously, following the theory of self-efficacy, the framework assumes that the constructive engagement from using the generative AI shapes students' confidence and their creative capabilities (Bandura 1997).

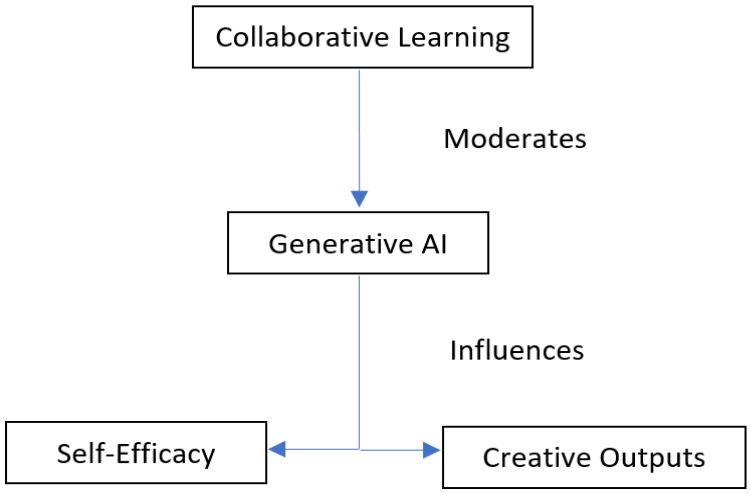


Figure 1. Conceptual Framework of AI-Supported Ideation in Product Design Education

Figure 1 illustrates the framework, which proposes that using generative AI during ideation can enhance creative output both directly and indirectly by strengthening students' self-efficacy. This process is further mediated by collaborative learning, where peers work collectively and interact with AI as a co-creative partner. A controlled experiment was conducted with fifty purposively selected product design students (Guest, Bunce, and Johnson 2006) from the Faculty of Applied and Creative Arts, Universiti Malaysia Sarawak, organised into five groups. Although product design education normally involves four phases (empathy, define, ideation, prototyping/testing), this study focused exclusively on ideation, as it is the stage where the generation of diverse possibilities is most critical. Generative AI is especially impactful here due to its capacity to generate rapid visual variations. The ideation process was operationalised across three structured phases, allowing for a focused examination of how AI influences creativity, collaboration, and self-efficacy during concept development. The study was not intended to replicate the full design cycle but to isolate AI's role within ideation. The "controlled" element was ensured by providing all groups with the same design brief, equal time allocation, standardised instructions, and a consistent environment to minimise external variables.

Phase 1: demonstration and brainstorming session

Phase 1 began with a 20-minute session designed to prepare respondents for the next stage. The research team demonstrated how to construct prompts and use ChatGPT 4.0 to generate visual outputs. Each group was given two reference sketches—a computer mouse and a bread toaster (see Table 1), and asked to analyse them to identify design features with potential for innovation.

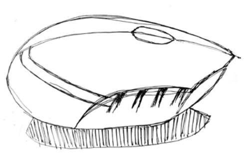
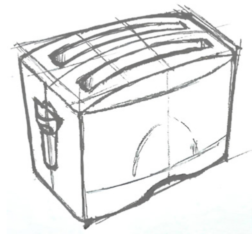
	
(a)	(b)

Table 1. Reference image (a) Computer mouse; (b) Bread toaster

Working collaboratively, groups developed prompts using three key elements: (1) the product subject, (2) intended innovative features, and (3) preferred style. For example, they described the base product (e.g., bread toaster in a kitchen cabinet), specified enhancements (e.g., touch controls with menu options), and added stylistic direction (e.g., futuristic appearance with hyper-realistic imagery). To maintain consistency, all prompts followed a standard structure, beginning with "Based on the given image…" and ending with "… hyper realistic photography." This approach allowed flexibility in interpretation while keeping the generated visuals focused and comparable across groups.

Phase 2: generating images

Phase 2 involved applying the prompts developed earlier to produce visual concept images using ChatGPT 4.0 (https://chatgpt.com/). Over a 30-minute session, students uploaded the reference sketches (computer mouse and bread toaster) and used structured prompts describing the subject, features, and style. The AI generated corresponding visuals. To reflect iterative design practice, each group of ten students was allowed up to ten prompt revisions to refine their results. All final prompts and selected images were recorded.

Visual Dimensions of Images		
Visual Value	Visual Performance	Image's Visually Dimension
A dimension reffered to the non-discursive characteristics of images which allows a simultaneous per ception of visual information	A dimension that indicates the ways visual signs are composed in an image or to what it is visually represented.	A dimension where the visual become an element of persuasiveness. It underlines both the importance of visual information in communication and the rhetorical power of images.
Purpose: to assess how well AI-generated features matched the intended design ideas.	Purpose: to evaluated how clearly and effectively the prompts shaped the image outcomes.	Purpose: to determine the overall image quality such as balance, harmony, and how closely it resembled the reference sketch.

Table 2. Visual dimension of images, adapted from Burri (2012)

In this study, image analysis referred to Mason and Burri's methods (Mason 2005; Burri 2012). Mason emphasized descriptive observation and organizing image plates linked to theory, while Burri identified three visual dimensions: (1) visual value, indicating immediate perceptual qualities; (2) visual performance, referring to how elements are structured; and (3) visual dimension, relating to emotional resonance or persuasive impact. These were consolidated into one framework (see Table 2). Visual value assessed how closely AI-generated elements aligned with intended concepts, visual performance examined the clarity and influence of prompts on outcomes, and the visual dimension evaluated image quality in terms of harmony, balance, and resemblance to the reference sketches.

Phase 3: debrief interview session

Phase 3 involved 20-minute debrief interviews to capture respondents' reflections on Phases 1 and 2. For Phase 1, the questions addressed: (1) their experience during the briefing, (2) clarity of instructions and demonstrations, and (3) the process of identifying design criteria. For Phase 2, the discussion focused on: (1) group confidence and teamwork in generating prompts, (2) experiences using ChatGPT 4.0 and refining outputs, and (3) perceptions of creativity and innovation in the AI-generated images.

ID	Respondent 1	Respondent 2	Respondent 3
Protocol Time	05:18	03:41	07:25
Transcriptions	"The briefing was very thorough. The instructions on how to generate and use prompts were clear, and the examples really helped me understand the process."	"I appreciated the detailed document provided. The step-by-step guidance on using ChatGPT 4.0 was especially helpful."	"I found the session quite informative. It was my first time working with generative AI. and the demonstrations made it much easier to grasp."
Attributes	• Briefing was very thorough. • Instructions were clear. • The examples are good.	• The document is detail. • The guidance of using ChatGPT 4.0 is effective.	• The briefing was informative. • The demonstration is effective.
Open Codes: Categories of information	Respondent had a thorough briefing, clear instructions, and good examples during the briefing session.	Respondent bad a good guidance on ChatGPT 4.0 with detailed document.	The briefing and demonstrations help the respondent.
Axial Codes	Respondents' experience during the briefing session is considered good due to a thorough briefing, clear instructions, and good examples during the briefing session.	Respondents' experience during the briefing session is considered good due to a good guidance on ChatGPT 4.0 with detailed document.	Respondents' experience during the briefing session is considered good due to the effectiveness of briefing content and demonstrations.
Selective Codes	Respondents' experiences during 1he briefing session were considered positive due to be thoroughness of the briefing, the clarity of instructions, the quality of examples provided, the detailed guidance on using ChatGPT 4.0, and the overall effectiveness of the briefing content and demonstrations.		

Table 3. Sample of coding on three respondents' experiences during the debrief interview session

Table 3 (prev. page) illustrate the sample of coding on three respondents' experiences during the debrief interview session. The interview data were analyzed using a three-step coding process: open coding, axial coding, and selective coding (Creswell 2009; Saldaña 2015). This method helps organize qualitative data into meaningful categories. In open coding (see Table 3), key parts of respondents' responses were labeled and broken into smaller pieces. During axial coding, these labels were grouped into broader categories by identifying connections between them. Some codes were reorganized or refined to better fit emerging ideas. In the final step, selective coding, the researcher identified the most important themes by looking at how the categories were related. This step was sometimes repeated to adjust previous codes when new insights appeared. This stage also involves deciding which themes are most relevant to the research goals (Muller and Kogan 2012). By the end of the process, only the key themes were kept, giving a clear summary of respondents' experiences and feedback.

Data findings and discussions

The AI-generated visuals in Table 4 and 5 reflected how well each group collaborated in crafting prompts. Groups 1 and 4 consistently produced coherent outcomes, such as Bauhaus and Japanese minimalist toaster concepts and computer mouse designs incorporating ergonomic curves, lighting effects, or superhero-inspired colour schemes. Their success aligns with Johnson and Johnson's cooperative learning model, as shared regulation and collective refinement led to clearer AI instructions (Johnson and Johnson 1989). Conversely, Groups 2 and 3 frequently omitted essential features such as safety elements, colour variation, large bread capacity, or themed illumination, highlighting that AI creativity depends on iterative prompting rather than automation. This supports Glăveanu's view of distributed creativity emerging through human–technology interaction (Glăveanu 2014; Glăveanu 2021). Overall, this study examines how design prompts (particularly the subject, function, and style) shaped AI-generated outputs, underscoring the need for clear and imaginative prompt construction. Emphasis on innovative features allowed the analysis of how well AI translated functional and conceptual intent. The findings reveal both the potential and limits of AI in stimulating creativity,

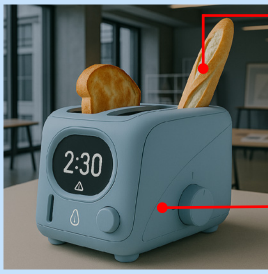
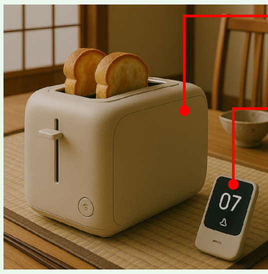
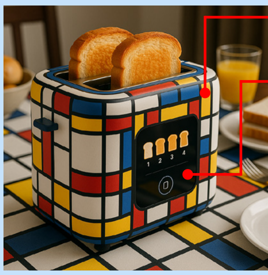
Input Prompt	Prompt Synthesis	Generated AI Image	Descriptive Analysis of Generated Image
Group 1: Based on the given image, generate an image of bread toaster at a dining area. The bread toaster has a compartment for honey jam and butter. In the style of Bauhaus and hyper realistic photography	• Subject: bread toaster at a dining area • Description: compartment for honey jam and butter • Style / Aesthetic: Bauhaus and hyper realistic photography		• Bread toaster at a dining area was generated • Compartment for honey jam and butter was successfully included. • The Bauhaus style was successfully captured the element of minimalism.
Group 2: Based on the given image, generate an image of bread toaster on a dining table at luxury restaurant. The bread toaster has a futuristic timer, temperature adjuster, and safety elements from excessive heat. In the style of Zaha Hadid and hyper realistic photography	• Subject: bread toaster on a dining table at luxury restaurant • Description: futuristic timer, temperature adjuster, and safety elements from excessive heat • Style / Aesthetic: Zaha Hadid and hyper realistic photography		• Bread toaster on a dining table at luxury restaurant was generated. • The futuristic timer and temperature adjuster were generated. The safety elements from excessive heat were poorly implemented on the styling form. • The styling form successfully imitates Zaha Hadid's influence.
Group 3: Based on the given image, generate an image of bread toaster on design studio pantry. The bread toaster has a space for multiple type of breads such sourdough and baguette, safety timer controller and touch screen. In the style of futuristic and hyper realistic photography	• Subject: bread toaster on design studio pantry • Description: space for multiple type of breads such sourdough and baguette, safety timer controller and touch screen • Style / Aesthetic: futuristic and hyper realistic photography		• The space for multiple type of breads such sourdough and baguette were poorly generated. • The safety timer controller and touch screen were successfully generated. • Bread toaster on design studio pantry was generated. • The futuristic styling form was successfully generated with light blue color.
Group 4: Based on the given image, generate an image of bread toaster on Japanese inspired dining table. The bread toaster has a wireless timer controller and remote-control screen. In the style of Japanese and hyper realistic photography	• Subject: bread toaster on Japanese inspired dining table • Description: wireless timer controller and remote-control screen • Style / Aesthetic: Japanese and hyper realistic photography		• Bread toaster on Japanese inspired dining table was generated. • Wireless timer controller and remote-control screen were generated. • The Japanese style was successfully generated with the element of simplicity.
Group 5: Based on the given image, generate an image of bread toaster on contemporary dining table. The bread toaster has a touch control with bread toast menu options. In the style of de Stijl and hyper realistic photography	• Subject: bread toaster on contemporary dining table • Description: touch control with bread toast menu options • Style / Aesthetic: de Stijl and hyper realistic photography		• Bread toaster on contemporary dining table were generated. • Touch control with bread toast menu options were generated. • The de Stijl style was successfully generated with the iconic color palette

Table 4. Findings of image-based analysis (bread toaster) from the outcomes of Phase 2

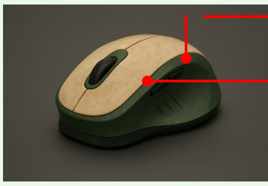
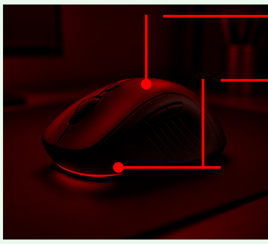
Input Prompt	Prompt Synthesis	Generated AI Image	Descriptive Analysis of Generated Image
Group 1: Based on the given image, generate an image of computer mouse on the office table. The computer mouse has a features of ergonomic handl ng and sensor colour variations. In the style of superheroes and hyper realistic photography	• Subject: computer mouse on the office table • Description: ergonomic handling and sensor colour variations • Style/Aesthetic: superheroes and hyper realistic photography		• Computer mouse on the office table was generated • The features of ergonomic handling and sensor colour variations was successfully included. • Superheroes style was successfully captured using the iconic Superman's blue and red colors.
Group 2: Based on the given image, generate an image of computer mouse on the gaming table. The computer mouse has a features of wireless technology, ergonomic handling, and form inspired from Renaissance art. In the style of minimalist and hyper realistic photography	• Subject: computer mouse on the gaming table • Description: wireless technology, ergonomic handling, sensor colour variations, and form inspired from Renaissance art • Style/Aesthetic: minimalist and hyper realistic photography		• Computer mouse was generated but not on the gaming table • Wireless technology and ergonomic handling was generated but the sensor colour variations was not generated and a form inspired from Renaissance art were poorly implemented. • The overall image illustrate the element of minimalist
Group 3: Based on the given image, generate an image of computer mouse on the Chinese inspired table. The computer mouse has a features of ergonomic handling, wireless, Chinese pattern and disco colour lighting. In the style of Art Nouveau and hyper realistic photography	• Subject: computer mouse on the Chinese inspired table • Description: ergonomic handling, wireless, Chinese pattern , and disco colour lighting • Style/Aesthetic: Art Nouveau and hyper realistic photography		• Computer mouse on the Chinese inspired table was generated. • Ergonomic handling, wireless, Chinese pattern were generated but not the disco colour lighting • The element of Art Nouveau was successfully generated.
Group 4: Based on the given image, generate an image of computer mouse on the table in design studio. The computer mouse has a features of sensor with menacing lighting colour, wireless technology, and ergonomic handling. In the style of menacing red and hyper realistic photography	• Subject: computer mouse on the table in design studio • Description: sensor with menacing lighting colour, wireless technology, and ergonomic handling • Style/Aesthetic: menacing red and hyper realistic photography		• Computer mouse on the table in design studio was generated. • Sensor with menacing lighting colour, wireless technology, and ergonomic handling were generated. • Menacing red as an environment was succesfully generated
Group 5: Based on the given image, generate an image of computer mouse on the gaming table. The computer mouse has a features of wireless technology, ergonomic design, futuristic colours lighting. In the style of Japanese Samurai and hyper realistic photography	• Subject: computer mouse on the gaming table • Description: wireless technology, ergonomic design, futuristic colours lighting • Style/Aesthetic: Japanese Samurai and hyper realistic photography		• Computer mouse on the gaming table were generated. • Wireless technology, ergonomic design, futuristic colours lighting were generated. • The element of Japanese Samurai was successfully generated but not literally.

Table 5. Findings of image-based analysis (computer mouse) from the outcomes of Phase 2

encouraging experimentation, and fostering collaborative self-efficacy. Through AI-supported collaboration, students explored ideas more freely and gained deeper insight into product innovation and customization. AI acted not as a substitute for creativity but as a mediating tool that enhanced ideation through co-construction and iterative collaboration.

Table 6 summarize thematic coding matrix linking participant quotes to theoretical constructs from the debrief interview. Re-

Transcriptions	Open Codes (Initial Concept Label)	Axial Coding (Grouped Category)	Selective Coding (Core Theoretical Construct)
"The briefing session helped reduce my anxiety because everything was explained step-by-step in a very friendly manner."	Felt reassured.	Positive emotional response to instruction.	Self-efficacy development (Bandura 1986)
"Watching the live demonstration made it much easier to understand compared to only looking at written instructions."	Preferred demonstration-based learning	Visual & experiential scaffolding	Instructional clarity / Cognitive readiness
"Identifying the design criteria before writing prompts forced me to think more carefully about function, material, and style."	Structured thinking before prompting	Metacognitive planning	Creative problem framing (Creativity process)
"Working in pairs to write prompts helped me gain confidence because we could build on each other's ideas instead of thinking alone."	Mutual idea exchange	Collaborative negotiation	Cooperative learning (Johnson & Johnson 1989)
"Refining the prompt felt like solving a puzzle because every small change produced a different AI output."	Iterative experimentation	Trial-and-error refinement	Mastery through iteration (Self-efficacy spiral)
"The Al sometimes added details I did not expect, but those surprises actually made the design more innovative than I originally imagined."	Al as co-creator	Human-AI interaction expands ideas	Distributed creativity (Glăveanu 2014, 2021)

Table 6. The Summary of Debrief Interview: Thematic Coding Matrix Linking Participant Quotes to Theoretical Constructs

spondents reported highly positive experiences during the initial briefing session. Several respondents explained that "the briefing session helped reduce my anxiety because everything was explained step-by-step in a very friendly manner." This sense of reassurance created an early foundation of confidence, allowing respondents to engage with the AI tools without hesitation. Clarity of instruction played a major role in this effect. As one participant stated, "watching the live demonstration made it much easier to understand compared to only looking at written instructions," indicating that visual scaffolding supported comprehension more effectively than text-based guidance alone. When asked about identifying design criteria prior to writing prompts, many respondents acknowledged that the process deepened their analytical thinking. One reflected that "identifying the design criteria before writing prompts forced me to think more carefully about function, material, and style," suggesting that structured reflection led to more intentional design articulation. Collaboration also emerged as a critical factor in building confidence. As one respondent shared, "working in pairs to write prompts helped me gain confidence because we could build on each other's ideas instead of thinking alone." Respondent described their experience using ChatGPT 4.0 as iterative and exploratory. Rather than expecting perfect outputs on the first attempt, most adopted a problem-solving mindset. One participant explained that "refining the prompt felt like solving a puzzle because every small change produced a different AI output." This trial-and-error process positioned AI as a responsive collaborator rather than a passive generator. Finally, respondents consistently acknowledged the AI's capacity to extend their creativity. As one noted, "the AI sometimes added details I did not expect, but those surprises actually made the design more innovative than I originally imagined." The findings reveal that the structured briefing session and live demonstrations were pivotal in reducing anxiety, establishing early confidence and enabling students to engage with AI tools without hesitation. Clear visual guidance proved more effective than written instructions alone, supporting better comprehension and task readiness. Identifying design criteria before prompt creation encouraged deeper analytical thinking, prompting students to consider function, material, and style more intentionally. Collaboration further strengthened confidence, as working in pairs enabled idea sharing and reduced individual pressure. Participants also described their interaction ChatGPT 4.0 as an iterative, exploratory process, where refining prompts was viewed as problem-solving rather than trial-and-error. This positioned AI as an active co-creator rather than a passive tool. Importantly, respondents acknowledged that AI-generated outputs often introduced unexpected but valuable creative possibilities, enhancing innovation beyond their initial ideas.

Conclusion

This study explored the integration of generative AI in the ideation phase of product design education, focusing on its impact on creativity, self-efficacy, and collaborative learning. The findings show that AI supports rather than replaces human creativity, acting as a co-creative partner that helps students convert abstract ideas into rapid visual outputs. This demonstrates AI's value in translating imagination into tangible concepts. A key insight was the importance of structured onboarding. Demonstrations and guided briefing sessions equipped students with foundational skills, increasing confidence and readiness to experiment. Early scaffolding contributed to effective engagement, consistent with guided learning principles. The iterative nature of prompt development also revealed initial challenges in articulating ideas verbally. However, through collaboration and refinement, students improved their prompt engineering abilities and became more aware of how linguistic precision shapes visual results. The image-based outputs further showed that students were not passive users. They critically evaluated aesthetic, functional, and persuasive aspects of the visuals, using AI-generated images as stimuli for further ideation rather than as final solutions. This reflects design thinking practices and supports theories of co-construction and visual reasoning. Overall, the study demonstrates that generative AI can enhance ideation by amplifying creativity, building self-efficacy, and reinforcing collaborative engagement. It offers practical direction for educators seeking AI-augmented pedagogical strategies and lays groundwork for future research into implementation, ethics, platform comparison, and long-term creative development.

References

Bandura, Albert. 1986. *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ: Prentice Hall.

Bandura, Albert. 1997. *Self-Efficacy: The Exercise of Control*. New York: W.H. Freeman/Times Books/Henry Holt & Co.

Burri, Regula Valérie. 2012. "Visual Rationalities: Towards a Sociology of Images." *Current Sociology* 60 (1): 45–60. https://doi.org/10.1177/0011392111426647.

Chien, Yu-Hung, Kuen-Yi Lin, Hsien-Sheng Hsiao, Yu-Shan Chang, and Shaio-Chung Chan. 2022. "Measuring Industrial Design Self-Efficacy and Anxiety." *International Journal of Technology and Design Education* 32 (2): 1317–1336. https://doi.org/10.1007/s10798-020-09648-0.

Creswell, John W. 2009. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. 3rd ed. Thousand Oaks, CA: SAGE Publications.

Csikszentmihalyi, Mihaly. 1999. "Implications of a Systems Perspective for the Study of Creativity." In *Handbook of Creativity*, edited by Robert J. Sternberg, 313–335. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511807916.018.

Csikszentmihalyi, Mihaly. 1996. *Creativity: Flow and the Psychology of Discovery and Invention*. New York: HarperCollins.

Dillenbourg, Pierre. 1999. "What Do You Mean by Collaborative Learning?" In *Collaborative Learning: Cognitive and Computational Approaches*, edited by Pierre Dillenbourg, 1–19. Oxford: Elsevier.

Glăveanu, Vlad Petre. 2014. "Distributed Creativity: What Is It?" In *Distributed Creativity: Thinking Outside the Box of the Creative Individual*, 1-13. Cham: Springer. https://doi.org/10.1007/978-3-319-05434-6_1.

Glăveanu, Vlad Petre. 2021. *The Possible: A Sociocultural Theory*. Oxford University Press.

Guest, Greg, Arwen Bunce, and Laura Johnson. 2006. "How Many Interviews Are Enough? An Experiment with Data Saturation and Variability." *Field Methods* 18 (1): 59-82. https://doi.org/10.1177/1525822X05279903.

Hashmi, Nada, and Anjali S. Bal. 2023. "Generative AI in Higher Education and Beyond." *Business Horizons* 67 (5): 607-614. https://doi.org/10.1016/j.bushor.2024.05.005.

Huang, Kuo-Liang, Yi-Chen Liu, Ming-Qing Dong, and Chia-Chen Lu. 2024. "Integrating AIGC into Product Design Ideation Teaching: An Empirical Study on Self-Efficacy and Learning Outcomes." *Learning and Instruction* 92. https://doi.org/10.1016/j.learninstruc.2024.101929.

Johnson, David W., and Roger T. Johnson. 1989. *Cooperation and Competition: Theory and Research*. Edina, MN: Interaction Book Company.

Jonson, Ben. 2005. "Design Ideation: The Conceptual Sketch in the Digital Age." *Design Studies* 26 (6): 613–624. https://doi.org/10.1016/j.destud.2005.03.001.

Laal, Marjan, and Seyed Mohammad Ghodsi. 2012. "Benefits of Collaborative Learning." *Procedia – Social and Behavioral Sciences* 31:486–490. https://doi.org/10.1016/j.sbspro.2011.12.091.

Mason, Paul. 2005. "Visual Data in Applied Qualitative Research: Lessons from Experience." *Qualitative Research* 5 (3): 325–346. https://doi.org/10.1177/1468794105054458.

Mohamed Kamil, Muhammad Jameel, and Mohd Najib Abdullah Sani. 2021. "The Challenges and Initiatives of Teaching Product Design's Course Online During the COVID-19 Pandemic in Malaysia." *Asia Pacific Journal of Educators and Education* 36 (1): 113–133. https://doi.org/10.21315/apjee2021.36.1.7.

Mohamed Kamil, Muhammad Jameel, Nazratul Nadiah Samsuddin, Mohd Najib Abdullah Sani, and Amir Hassan Mohd Shah. 2024. "The Integration of Ergonomics Ergo-System Framework (EESF) with the Product Design Process in the Innovation Ergonomic Seating Support for Scoliosis Patients." *International Journal of Systematic Innovation* 8 (2): 44–57. https://doi.org/10.6977/IJoSI.202406_8(2).0004.

Muller, Michael J., and Sandra Kogan. 2012. "Grounded Theory Method in Human-Computer Interaction and Computer-Supported Cooperative Work." In *Human Computer Interaction Handbook.*, edited by Julie A. Jacko, 1003-1024. Boca Raton: CRC Press. https://doi.org/10.1201/b11963.

Nelson, Brent A., Jamal O. Wilson, David Rosen, and Jeannette Yen. 2009. "Refined Metrics for Measuring Ideation Effectiveness." *Design Studies* 30 (6): 737–743. https://doi.org/10.1016/j.destud.2009.07.002.

O'Malley, Claire. 1995. *Computer Supported Collaborative Learning*. Heidelberg: Springer-Verlag. https://doi.org/10.1007/978-3-642-85098-1.

Pajares, Frank, and Dale H. Schunk. 2002. "The Development of Academic Self-Efficacy." In Development of Achievement Motivation, edited by Allan Wigfield and Jacquelynne S. Eccles, 15–31. San Diego, CA: Academic Press. https://doi.org/10.1016/B978-012750053-9/50003-6.

Saldaña, Johnny. 2015. *The Coding Manual for Qualitative Researchers*. 3rd ed. London: SAGE.

Self, James, Mark Evans, and Eun Jin Kim. 2016. "A Comparison of Digital and Conventional Sketching: Implications for Conceptual Design Ideation." *Journal of Design Research* 14 (2): 171–202.

Short, Cole E., and Jeremy C. Short. 2023. "The Artificially Intelligent Entrepreneur: ChatGPT, Prompt Engineering, and Entrepreneurial Rhetoric Creation." *Journal of Business Venturing Insights* 19. https://doi.org/10.1016/j.jbvi.2023.e00388.

Tian, Yu, Ang Liu, Yun Dai, Keisuke Nagato, and Masayuki Nakao. 2024. "Systematic Synthesis of Design Prompts for Large Language Models in Conceptual Design." *CIRP Annals* 73 (1): 85-88. https://doi.org/10.1016/j.cirp.2024.04.062.

Tierney, Pamela, and Steven M. Farmer. 2002. "Creative Self-Efficacy: Its Potential Antecedents and Relationship to Creative Performance." *Academy of Management Journal* 45 (6): 1137–1148. https://doi.org/10.2307/3069429.

Vygotsky, Lev S. 1978. *Mind in Society: The Development of Higher Psychological Processes*. Edited by Michael Cole, Vera Jolm-Steiner, Sylvia Scribner, and Ellen Souberman. Cambridge, MA: Harvard University Press. https://doi.org/10.2307/j.ctvjf9vz4.

Ye, Yilin, Jianing Hao, Yihan Hou, Zhan Wang, Shishi Xiao, Yuyu Luo, and Wei Zeng. 2024. "Generative AI for Visualization: State of the Art and Future Directions." *Visual Informatics* 8 (2): 43–66. https://doi.org/10.1016/j.visinf.2024.04.003.

Zimmerman, Barry J. 2000. "Self-Efficacy: An Essential Motive to Learn." Contemporary Educational Psychology 25 (1): 82–91. https://doi.org/10.1006/ceps.1999.1016.