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Reflective Practices and Self-Regulated Learning in Designing with Generative Artificial Intelligence: An Ordered Network Analysis

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Abstract
Advances in generative artificial intelligence (AI) have enabled new forms of human-AI interaction. In this work, we explored the utility of using generative AI, specifically OpenAI's ChatGPT (Chat Generative Pre-trained Transformer) 3.5, to support the design thinking process to identify user needs, ideate, and refine solutions. We examined how 17 students and professionals from a design program engaged in reflective design practices and self-regulated learning (SRL), as they used generative AI to brainstorm ideas. We further explored how participants considered, elaborated upon, and integrated the AI-generated ideas into their design artifacts. Analyses involved qualitative coding of the brainstorming sessions and Ordered Network Analysis, which visualized the co-occurrences between reflective design practices and SRL as indicators of multifaceted learning engagement. Findings illuminate the importance of iterative evaluation and planning of AI-generated ideas, in conjunction with reflection on design moves, to improve design quality. We discuss the importance of reflective practices and SRL in AI-integrated learning.

Keywords Generative artificial intelligence · Large language models · Design thinking · Self-regulated learning · Network analysis

Introduction

Design thinking is integral to science, technology, engineering, and mathematics (STEM) practices as an analytic and iterative process to identify human needs, create solutions, collect feedback, and refine ideas (T. Li & Zhan, 2022; Razzouk & Shute, 2012; Strimel et al., 2019). Learners develop domain knowledge and creative problem-solving skills, through ideating and exploring solutions to complex, real-world problems (English, 2019; Koh et al., 2015; Nichols et al., 2022). However, facilitating design thinking is challenging. Facilitators need to ensure that designers consider the problem space from multiple perspectives, instead of jumping to conclusions (Henriksen et al., 2018). While reflexivity among designers to discuss and revisit ideas is linked to more successful idea generation (Seidel & Fixson, 2013), novice designers do not naturally engage in deep reflection (Björklund, 2013). Artificial intelligence (AI) tools have shown promise in promoting design thinking (Lai et al., 2023; Tholander & Jonsson, 2023). These tools can present novel ideas (Kim & Maher, 2023), help designers examine the perspectives of potential users (Zhang et al., 2016), and prompt reflection (Schleith et al., 2022). We build on these efforts to explore the use of generative AI to facilitate design thinking.

Generative AI (GenAI) technologies include Large Language Models that can produce novel text, images, and audio without extensive human instruction. These technologies hold promise in facilitating content creation and promoting creativity and learning across domains, such as writing, arts, and data science (Lin et al., 2020; D. Wang et al., 2019; Yang et al., 2022). For instance, writers using GenAI (GPT-4) to generate multiple ideas for short stories saw an increase in idea novelty, compared to those without AI access (Doshi & Hauser, 2024). Emergent research has positioned AI as a collaborator in ideating and creating artifacts (Karimi et al., 2020). Human-AI collaboration positions AI tools as dynamic agents that cooperate with humans toward

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shared goals (Terveen, 1995). The collaboration involves interaction and interdependent exploration of ideas between humans and AI (J. Li et al., 2022a, 2022b, 2022c; Rezwana & Maher, 2022).

To support human-AI collaboration in design contexts, we examine (1) how the collaboration augments *design practices*, and (2) how individuals *regulate* the AI-integrated workflow. Human-AI collaboration can influence design practices, as individuals consider and incorporate AI-suggested ideas while AI adapts to human's inputs (Lai et al., 2023). Importantly, integrating AI as a collaborator requires regulation. Given the vast amount of content AI can provide, learners need to iteratively evaluate the generated content to adapt their strategies (Järvelä et al., 2023; Yang et al., 2022).

Building on these assumptions, we focus on *reflective design practices* and *self-regulated learning* (Hong & Choi, 2011; Kavousi et al., 2020). Designers engage in reflective practices to consider past actions and generate new insights (Schön, 1983). These practices include *naming* task aspects, *framing* design focus, *moving* to brainstorm ideas, and *reflecting* on past decisions to reframe the design (Adams et al., 2003; Valkenburg & Dorst, 1998). In integrating AI as a collaborative ideator, designers employ self-regulated learning (SRL) to *define* tasks, *plan*, *enact strategies*, and *evaluate* AI's responses (Järvelä et al., 2023).

In the present research, we examine patterns of reflective design practices and SRL in collaborating with GenAI. We draw from audio and screen-recorded data of 17 designers (undergraduates, graduates, and professionals from a design program) brainstorming with ChatGPT 3.5 (Chat Generative Pre-trained Transformer), a GenAI application. We situate the research context in user experience and user interface (UX/UI) design—a STEM field that applies design thinking in developing software and products. Analyses rely on qualitative analysis of the audio transcripts and the design sketches participants produced after brainstorming. Our focus on reflective design practices and SRL positions learning engagement as multifaceted. We thus apply Ordered Network Analysis (ONA) (Fan et al., 2023; Tan et al., 2022) to examine how reflective practices and SRL co-occur during human-AI collaboration. We further conduct open coding of the think-aloud transcripts, prompts to, and responses of ChatGPT, to explore how participants discussed, elaborated on, and integrated AI-generated ideas into their design sketches. We present findings for the sample and three focal cases to illustrate distinct patterns of collaborating with AI.

Our findings have implications for learning analytics and AI-integrated learning environments. We demonstrate the use of ONA in analyzing the link between SRL, design practices, and design products. This analytic strategy provides nuanced insights into the process of human-AI collaboration. Furthermore, findings suggest the importance of reflective practices and SRL in AI-integrated learning. We find that iterative evaluation and planning of AI-generated ideas, in conjunction with reflection on design moves, can be linked to higher design quality. Findings highlight the need for learners to strategize and critically evaluate the generated information in learning contexts that incorporate emerging GenAI technologies.

Background

AI Tools Support Idea Creation and Refinement

AI tools are increasingly capable of augmenting human's cognitive abilities and assisting humans in creation and decision-making (D. Wang et al., 2019). Licklider (1960) wrote about the concept of "symbiotic computing", defined as cooperative interaction between human and computers. In Licklider's vision, computers can assist humans in problem formulation and decision-making. Recent advances have positioned AI as an idea co-creator in multiple domains, including science education, automated data science analysis, healthcare decision-making, writing ideation, and creative production (Cai et al., 2019; Cooper, 2023; Karimi et al., 2020; Lin et al., 2020; Yang et al., 2022). AI tools can help designers and engineers think more deeply and widely, present ideas, and build prototypes at low costs (Wu et al., 2021).

New forms of human-AI interaction are enabled by Large Language Models (LLMs)—deep learning models trained on large data sets to understand and generate human language. Example LLMs include GPT-3.5 and GPT-4, which are underlying models for OpenAI's ChatGPT (as of January 2024). Both models apply the Transformer architecture (Vaswani et al., 2017), to facilitate pre-training on extensive text data and fine-tuning for various tasks, including text summarization, generation, and question answering. ChatGPT's appearance as a chat interface invites users to engage in human-like, conversational exchanges with follow-up questions and idea refinement. The shared creativity that emerges from human-AI interaction is distinct from products that either human or AI could create alone (Rezwana & Maher, 2022). By interacting with a range of AI-generated ideas, individuals might enhance their creative thinking and problem-solving. To illustrate, Qadir (2023) demonstrated different applications of ChatGPT to provide writing support, assist with research processes, and create and solve technical problems in engineering design. Researchers have proposed using LLMs across design phases, to solicit information about design contexts, define user needs, generate ideas, and simulate data to support usability testing (Schmidt et al., 2024).

Users' ongoing reflection and evaluation of AI's outputs are critical in AI-integrated creative tasks (Chung et al., 2022; Jung & Cho, 2022; Yang et al., 2022). In those tasks, the AI tools take on assistive roles rather than making decisions for the users (Louie et al., 2020). AI for creative processes may suggest novel or surprising details, and users reflect on how these details augment their designs (Jiang et al., 2021; Jung & Cho, 2022). For instance, AI co-writing tools can append or suggest new text based on the users' input (Clark et al., 2018; Yang et al., 2022). Computer vision systems reveal details that are hidden or confusing to photographers, ultimately expanding the way that they derive meanings from images (Jung & Cho, 2022). These examples illuminate how users critically evaluate the AI's outputs to refine ideas. The importance of reflection and evaluation in AI-integrated tasks guides our dual focus on (1) how users engage in reflective design practices as part of ideating with AI, and (2) how they evaluate AI responses.

Reflective Design Practices

Reflective design practices is central to design thinking (Hong & Choi, 2011). Reflective practices draw from the notion of reflection-in-action, where designers reflect on the constraints and requirements of the design space (Schön, 1983). Design ideas evolve in connection with contexts, research, and theory (Sadokierski, 2020). Across science and engineering disciplines, designers draw from and develop professional knowledge in the moment to analyze the situation, develop understanding, and make decisions (Adams et al., 2003; Schön & Wiggins, 1992). Valkenburg and Dorst (1998) proposed four reflective practices building on reflection-in-action: *naming*, *framing*, *moving*, and *reflecting*. Designers highlight task aspects and requirements (*naming*); decide on a specific concept, problem, or solution (*framing*); ideate, gather, summarize, and sort information (*moving*); and evaluate prior actions to reframe the design (*reflecting*) (Valkenburg & Dorst, 1998).

Iterating between practices is integral to both individual and collaborative design processes (Paton & Dorst, 2011; Stompff et al., 2016). Recurring practices (such as repeated segments of framing) have also been positively associated with more successful designs (Tang et al., 2012). We posit that AI interactions might influence the occurrences and sequences of reflective practices. This is because these practices emerge when the designers face surprise and uncertainty (Adams et al., 2003; Stompff et al., 2016), such as when AI tools propose novel information. In those instances, designers leverage their experience, knowledge, and understanding of the design context to evaluate the AI's responses. This evaluative process mirrors the metacognition employed in self-regulated learning. We turn to self-regulated learning to understand how designers navigate AI's responses.

Self-Regulated Learning

Learners monitor their own learning toward self-determined goals in self-regulated learning (SRL) (Azevedo et al., 2010; Greene & Azevedo, 2007). SRL is signified by the learners' proactive engagement in their own learning processes. It encompasses one's thoughts, feelings, and actions that are planned and cyclically adapted toward achieving personal goals (Zimmerman, 2002). SRL significantly contributes to the development of strategically competent learners (Pintrich, 2000).

We characterize SRL using the COPES model, which comprises five main components: **C**onditions, **O**perations, **P**roducts, **E**valuations, and **S**tandards (Winne & Hadwin, 1998). Conditions describe the task (e.g., resources, time, instructional cues) and individuals' cognitive conditions (e.g., motivation, belief, knowledge). Operations encompass the cognitive, metacognitive, and motivational processes employed when undertaking a task. Products are the outcomes of Operations. They can be cognitive, like a schema or mental model, or metacognitive, like awareness of one's understanding. Products are iteratively evaluated, to determine whether the learning objectives have been met. Evaluations can originate from learners' reflections or external entities, such as instructors or peers. Finally, learners rely on Standards to monitor their progress. The standards can be internal (e.g., personal goals) or external (e.g., curriculum requirements).

The model also delineates four phases of SRL, with each phase occurring through interactions between the five COPES components: *task definition*, *planning and goal setting*, *studying tactics*, and *evaluation and adaptation.* Most learning involves engaging with conditions to define the task (task definition), followed by determination of goals (planning and goal setting) and strategy enactment (studying tactics). The resulting products are then compared against standards, task conditions, and learners' beliefs (evaluation). Such evaluation can lead to more substantial revisions of one's beliefs, motivation, and tactics (adaptation).

Learners engage in dynamic SRL processes in AI-integrated contexts (Cukurova, 2024; Järvelä et al., 2023; Molenaar, 2022) and with GenAI (A. Nguyen et al., 2024). In using AI, one may iteratively evaluate the ideas that human and AI create, adapt and integrate AI-generated ideas, and continually shape their learning trajectory (X. Wang et al., 2023). Researchers have examined SRL in human-AI collaboration (Molenaar, 2022; A. Nguyen et al., 2024). AI-powered tools can provide real-time feedback and interaction, promoting greater metacognitive awareness and self-regulation (Molenaar, 2022). The interaction between human and AI positions the technology as a partner that can adapt to individual learners' needs—opening new venues for developing sophisticated SRL (A. Nguyen et al., 2024).

Studying Multifaceted Learning through Ordered Network Analysis

Our theoretical frameworks—focusing on reflective design practices and SRL—position learning as multifaceted. We thus employ ordered network analysis (ONA) techniques, to examine learning as networks of co-occurring strategies, knowledge, and values (Tan et al., 2022). ONA builds on prior approaches like Epistemic Network Analysis (ENA) (Shaffer & Ruis, 2017). ENA identifies and visualizes connections among components in coded data as network models (Shaffer & Ruis, 2017). The models illuminate the structure and strength of connections between components, to provide insight into supporting design thinking (Arastoopour Irgens, 2021; Elmoazen et al., 2022) and SRL (S. Li et al., 2022a, 2022b, 2022c; Saint et al., 2020, 2021) in education contexts.

While ENA aggregates connections between codes across the data set, emergent research has attended to the sequential and directed nature of learning, when an activity more frequently precedes another within the same timeframe (Brohinsky et al., 2021; Fan et al., 2023; Melzner et al., 2019; H. Nguyen et al., 2021). ONA extends ENA to emphasize (1) the directions of co-occurrences, and (2) self-loops when a learning activity repeats itself. The co-occurrences of knowledge components and strategies within a specific window of discourse can indicate cognitive, metacognitive, and motivational links (Fan et al., 2023; S. Li et al., 2022a, 2022b, 2022c). Such analyses can provide additional insights into the flow of learning activities (Brohinsky et al., 2021). They also illuminate the role of specific elements within a network, such as the influence of evaluative actions on a student's learning strategy.

Methods

While AI tools have demonstrated promises in supporting design ideation and refinement, it is critical to consider how collaboration with AI augments design practices and support self-regulation. The questions that guide our research are: ***RQ1:*** *What are patterns of reflective design practices and self-regulated learning in collaborating with a generative AI (GenAI) tool?* ***RQ2:*** *How are these patterns linked to the design thinking artifacts produced after human-AI collaboration?*

Study Settings and Participants

Data came from interviews with 17 designers with varied backgrounds: six undergraduate, four graduate students (3 master's, 1 s-year PhD), and seven alumni in a design program in a public university in the Mountain West United States. All alumni were working as professionals in UX/UI (three individuals) and instructional design fields (four individuals). The recruitment message invited individuals who were curious about applying GenAI tools in design contexts. This sampling strategy aligned with our focus on lifelong learning—self-driven knowledge pursuit to enhance human development—in the age of AI (Poquet & De Laat, 2021).

Participants interacted with OpenAI's ChatGPT (https://chat.openai.com, using GPT-3.5 at the time of data collection). Relying on deep learning architecture, the model is pre-trained on vast amounts of data to understand language patterns and can now generate human-like, conversational text responses (Brown et al., 2020). All but one participant had interacted with ChatGPT before the study. Most participants described personal uses (e.g., writing a poem or story), and about one-third described design-specific uses like brainstorming ideas and generating design templates. We did not fine-tune or provide upfront instructions to ChatGPT, to explore how individuals naturally engaged with the tool.

The interviews were about 45 min on average and took place via Zoom in May–June 2023 (institutional IRB #13497). They were audio- and video-recorded. The transcripts were automatically generated and checked by authors. During the interview, participants were introduced to the task: Redesign the navigation of Canvas, a learning management system that participants were familiar with as students and designers. They brainstormed the design task individually to identify design problems, users, and initial design ideas (10 min), before refining these ideas with ChatGPT (15–20 min). Both brainstorming sessions involved think-aloud protocols. The interactions with ChatGPT, where participants articulated their questions, thought processes, and reactions, were screen-shared and recorded. Participants then had 5–7 min to sketch design ideas independently (on paper or tablet), present the sketches verbally, and upload pictures of their sketches to share with the interviewers. Finally, they debriefed with the interviewers (3 min) and answered questions such as "What did you think about working with ChatGPT?" and "How would you improve the interactions to use ChatGPT in design?" The purpose of the debrief was to understand the interactions with GenAI from participants' perspectives.

Data Sources

In this paper, we focused on the brainstorming sessions, where participants were thinking aloud as they interacted with ChatGPT. We considered participants' think-aloud utterances at the sentence level as the main unit of analysis. Each transcript generated 88.53 utterances on average ($SD = 32.32$) for the brainstorming sessions.

We built on prior work to develop a codebook for reflective practices (Tang et al., 2012; Valkenburg & Dorst, 1998). We considered practices concerning both designers' activities and interactions with ChatGPT, given that reflective practices emerged from considerations of past actions and evolving design environments (Schön, 1983). Two members of the research team coded two transcripts separately to refine the code definitions. Table 1 provides the codes, examples, and inter-rater agreement (Cohen's κ) based on a third transcript. We also coded utterances for SRL activities in interactions with ChatGPT. Here, we drew from the phases in the COPES model, namely task definition, planning, tactics, and evaluation and adaptation (Winne & Hadwin, 1998). Table 1 describes the codes and reports the inter-rater agreement using two transcripts. A researcher coded the remaining data. Each utterance received one code for reflective practices and one code for SRL activities.

Additionally, we developed a rubric to code the design sketches that participants produced independently after brainstorming with ChatGPT. The rubric included four categories: *novelty*, *usefulness*, *elaboration*, and *incorporation of human's and AI's ideas*. The focus on novelty and usefulness was grounded in conceptualization of creativity in product design (Runco & Jaeger, 2012). Elaboration refers to the extent to which designers provided details to actualize the solution (Daly et al., 2016). We further considered human-AI idea incorporation, or the extent to which designers elaborated on and integrated both idea sources. This rubric category aligned with our focus on human-AI collaboration and the creative products emerging from the interaction between designers and AI (Rezwana & Maher, 2022). We measured each category on a scale of 0–5, with 0 = not present, and higher scores of 1–5 indicate higher quality. See Fig. 1 for an illustration of the rubric.

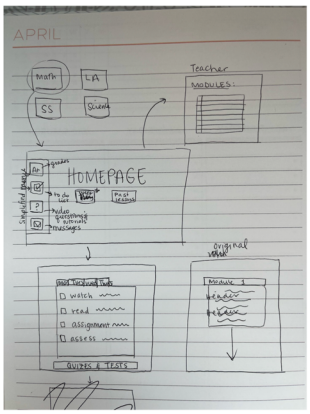
Two coders unfamiliar with the current study reached inter-rater agreement on 29% of the design sketches. They gave the same scores for the categories 90% of the time. The coders collaboratively scored the remaining sketches and discussed discrepancy. We calculated the total scores per participant for the four categories ($M = 10.58$; $SD = 2.49$; range 6–15). We used the median score of 11 as the cutoff for the two groups: those with relatively higher scoring sketches and others (higher-scoring: M sketch score = 12.39, $SD = 1.50$; lower-scoring: M sketch score = 8.54, $SD = 1.63$). The groups had a balanced distribution of designers, higher-scoring: three undergraduates, two graduates, and four professionals (three UX/UI; one instructional designer); lower-scoring: three undergraduates, two graduates, and three instructional design professionals.

Arguably, participants might not incorporate the AI's text into the final design sketches if they perceived the suggestions as irrelevant or unhelpful. We thus conducted an additional analysis of the design quality using the first three categories (*novelty*, *usefulness*, *elaboration*). The average score per participant in the new analysis was 8.58, $SD = 1.98$, range 4 to 11 (out of 15). Using the median score of 9 as the cutoff, we did not observe changes in assignment to the higher-scoring ($M = 10.06$, $SD = 1.07$) and lower-scoring groups ($M = 7.04$, $SD = 1.44$).

Table 1 Coding scheme, frequencies (n), and inter-rater agreement (Cohen's κ) for reflective practices and SRL

Code	Definition	Example	*n*	κ
Reflective practices				
name	State or clarify design steps	So, the task is about navigation	66	1
frame	Focus on subproblems/solutions	I'd look at what features are missing	173	0.93
move	Discuss concepts, brainstorm, gather information from AI's suggestions	[prompt ChatGPT] is there another way to connect the calendar event?	341	0.77
reflect	Consider earlier actions by the designer or AI and the fit with design vision	So [ChatGPT] said color coding. I might note how to color-code by situation	247	0.78
SRL				
define	Clarify requirements; interpret instruction about working with the AI	Remind me of the task again? What do you want me to do [with AI]?	39	1
plan	Plan the design steps and how to work with the AI for the task	You can have it role-play, like an experienced UX designer	383	0.74
tactics	Summarize, elaborate on, select information generated by the AI	[reading AI-generated text] A thread is not being organized, difficulty finishing tasks	392	0.94
evaluate	Evaluate AI's responses; compare responses to goals, standards, and experiences; adjust strategies	This is not helpful. Let's change the prompt [to AI]	331	1

Idea Description: A more simplified, easier to navigate version of Canvas dashboard … divided by subject … swapping the to-do list up and having it in calendar views. I also included video help and FAQs. And I added a "message the teacher" button. […] Originally, I was thinking to condense the sidebar menu, but ***talking to ChatGPT made me realize that the problems came from navigating Canvas***. So I added the video questions and tutorials. When I started talking about special education educations and ***we did the user profiles [for ChatGPT], I thought of accessibility*** because it's annoying for my special education students to scroll so much even for one week, so then I thought of the whole week layout.



Novelty (0 = solution already exists; 5 = solution is entirely different from what exists)
Score of 2 (the main solution of swapping or omitting sessions already exists).

Usefulness (0 = does not address prompt; 5 = solves the design problem effectively)
Score of 5 (solves the problem of navigation; considers several use cases for higher education as well as special education students in K-12).

Elaboration (0 = does not include details; 5 = includes enough detail that a designer could implement the solution)
Score of 4 (includes sufficient details in sketches and verbal descriptions for the sidebar menu; needs more details about the FAQ feature and implementation).

Idea Incorporation (0 = does not include AI conversations; 5 = incorporates several points from conversations into solution)
Score of 3 (brings in icons and use cases from conversations with AI; largely one's own thinking about the sidebar menu).

Fig. 1 Design sketch rubric

Analytical Procedures

Patterns of Reflective Design and SRL

To answer the RQs, we compared engagement in SRL and reflective practices between the higher-scoring and lower-scoring groups using Ordered Network Analysis (ONA) (Fan et al., 2023; Tan et al., 2022). The reflective practices and SRL codes were visualized as nodes in network graphs. Co-occurrences between nodes (connecting lines in the graphs) represent interconnection between design and self-regulatory components. ONA also visualizes directed connections between pairs of co-occurring actions, or when an action precedes another, to denote temporal progression. We determined a moving window of size four, to capture co-occurrences and connections within four utterances. We used means rotation to project the networks onto a two-dimension space, where the dimensions relate to differences between the comparison groups (Bowman et al., 2021).

The ONA graphs include multiple properties: node frequencies, self-loops, and directed connections. The size of the nodes indicates their frequencies, with larger node sizes indicating higher frequencies. The colored circles within each node represent self-loops when a learner continues staying in a reflective practice or SRL activity. Additionally, the arrows show the directed connection between two nodes.

Figure 2 illustrates these properties in the ONA graph for all participants. The figure shows that "tactic", "move", and "evaluate" were the most frequent and "name" and "define" the least frequent (indicated by the size of the black nodes). We observed frequent self-loops for "tactics", "move", and "plan", as noted by the gray circles for these nodes. Additionally, "evaluate" and "move" frequently co-occurred, with "evaluate" more often following "move" (shown by the arrow leading to evaluate). We visualized the networks of the higher-scoring and lower-scoring groups and created a subtraction network (subtracting the nodes and connections of the groups' networks) to highlight the differences between groups.

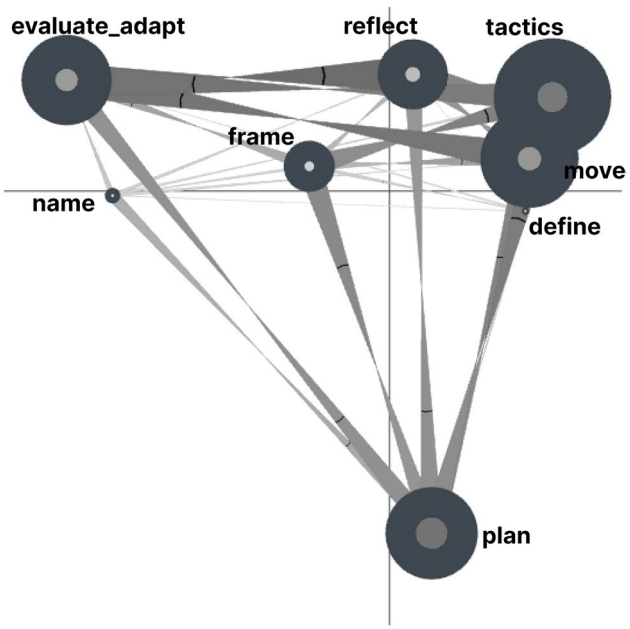


Fig. 2 Ordered network analysis for all participants

Case Studies

To further illuminate human-AI collaboration patterns and their connections to the design sketches (RQ2), we used a case study approach focusing on three participants entering their third and fourth year of the undergraduate degree (Eli, John, and Maya; pseudonyms). Participants had similar design background, with no external internship experiences. They spent similar amount of time brainstorming with ChatGPT (12–15 min). Eli and John scored high in the design sketches produced after human-AI collaboration (13 out of 20, respectively; max score 16), while Maya had a lower-scoring design (9/20).

We visualized the ordered network of design practices and SRL, to demonstrate distinct patterns of collaborating with GenAI. We observed creative uses of ChatGPT and multiple iterations of evaluation and planning for Eli and John. In contrast, Maya considered the AI's suggestions marginally and did not reach an elaborated design at the end of the section.

Additionally, we conducted open coding of the think-aloud transcripts, prompts to and responses of ChatGPT, and the design sketches participants produced after brainstorming. We presented narratives of key ideas emerging from ChatGPT's responses, and the extent to which Eli, John, and Maya *highlighted*, *elaborated* on, and *integrated* these ideas into their design sketches (Table 2). These codes provided deeper insights into the different ways that participants used ChatGPT in their design.

Findings

Reflective Practices and Self-Regulated Learning

To answer RQ1 about patterns of reflective practices and SRL, we first present descriptive statistics of the sessions. *Moving* was the most frequent reflective practices ($n = 341$; 22.66% of utterances), followed by *reflecting* ($n = 247$; 16.41%), *framing* ($n = 173$; 11.50%), and *naming* ($n = 66$; 4.39%). For SRL, engaging in *tactics* was the most frequent occurrence ($n = 392$; 26.05%). Participants employed various tactics, including summarizing information, asking questions, brainstorming, and elaborating on ideas. They also *planned* the design steps ($n = 383$; 25.45%), *evaluated* task progress and AI's responses towards the design goals ($n = 331$; 22.00%), and *defined* the tasks through questions and idea articulation ($n = 39$; 2.59%). Mann–Whitney U tests suggested difference in the occurrence of evaluation between the higher-scoring and lower-scoring groups (high: $M = 24.78$; $SD = 11.65$; low: $M = 13.50$; $SD = 3.66$; $p = 0.02$).

We further examined these patterns through their co-occurrence with reflective practices. For this, we ran ONA and compared the networks of the two groups, higher-scoring and lower-scoring in design sketches (Fig. 3). This analysis allowed us to answer RQ2, linking patterns of reflective practices and SRL to the quality of the design artifacts.

A Wilcoxon signed rank test for distributions of projected points between groups suggested difference on the first dimension (high: $M = -0.16$, $SD = 0.23$; low: $M = 0.19$, $SD = 0.17$; $z = -2.96$; $p = 0.002$). This means that participants who scored higher in their design sketches engaged in more *evaluation*, in conjunction with and following *reflection* to reframe the design, compared to those with lower-scoring sketches. The higher-scoring group also engaged in more self-loops of evaluation and reflection, as indicated by the larger colored circles (Panel C, Fig. 3). Meanwhile, the lower-scoring group engaged in more *tactics* and *move* to gather information, summarize ideas, and brainstorm design solutions.

To contextualize these findings, consider the following excerpts from Eli (higher-scoring group; Table 3). The table denotes the prompts that Eli sent to the AI, the AI responses, and Eli's sensemaking of the responses. Eli iteratively *evaluated* the ideas suggested by ChatGPT to expand the design space (bolded text indicates ideas from the AI's suggestions) and *reflected* on how they overlapped with her design visions ("that's more of what I was thinking").

For RQ2, we further explored the different strategies for collaborating with AI through three cases, Eli, John, and

Table 2 Consideration of AI-generated ideas

Code	Definition	Example
Highlight	Mention AI's ideas, by reading out loud the response aspects that stand out	"Progress tracking, that's interesting."
Elaborate	Consider the AI's ideas and their feasibility within the design context Combine AI's ideas with individual's design vision	"The number 3 is interesting too, where the system automatically can pull the information … **That's more of what I was thinking**, but like that **with the dynamic updates**, we would be really good."
Integrate	Integrate AI's ideas into final design	"One of the ideas that it [ChatGPT] brought up was accessibility. **That made me consider** the whole week layout to simplify things."

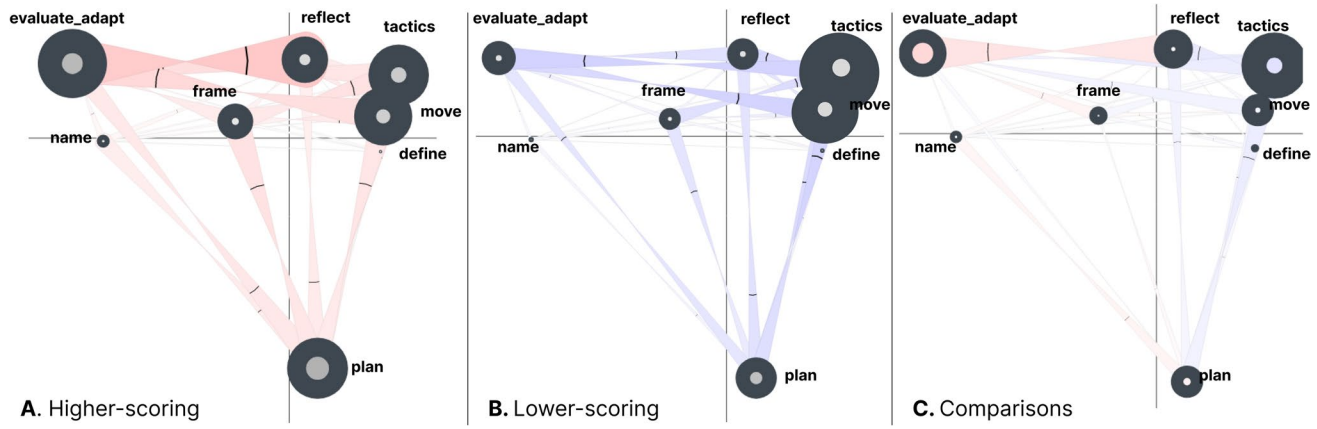


Fig. 3 Ordered networks comparing higher-scoring and lower-scoring groups

Table 3 Eli's prompts, AI responses, and think-aloud with ChatGPT

Prompt to AI	Is there a way to connect the calendar events with information on the syllabus?
AI responses	Yes. Here are a few ways to achieve this integration: 1. Linking: Within the calendar event description or details, you can include hyperlinks […] 2. Attachments: If your LMS (such as Canvas) supports file attachments […] 3. Dynamic syllabus updates: If the syllabus is subject to changes throughout the course, ensure that updates are reflected in the calendar events. […]
Think-aloud	The **dynamic syllabus** stands out where, if something is updated that it is reflected in the events And the **calendar feed subscription** is also interesting. It would be most beneficial to have that for bigger assignments. […] The number 3 is interesting too, where the system automatically can pull the information from the syllabus. **That's more of what I was thinking**, but like that **with the dynamic updates**, we would be really good
Prompt to AI	What changes can students make to the teachers' events to create an arbitrary due date?
AI responses	In general, students may not have the ability to directly change or create arbitrary due dates. However, here are a few suggestions: 1. Personal calendar. Students can maintain a personal calendar or planner outside of the LMS 2. Task management tools. Utilize task management applications that allow students to create their own tasks and due dates 3. Custom event types. Some LMS may allow students to create custom event types or labels within their personal calendar 4. Event descriptions: Students can add notes or comments to indicate that a due date is arbitrary or self-imposed […]
Think-aloud	My train of thought with this is it would be cool, you could take that event and set a personal due date. And then, have it locked where it can't go past the due date of the teachers. I mean, the **personal calendar**, you could create your own event. I use a personal calendar. But the **event description** is **kind of close to what I was thinking**

Case Studies: Different Patterns of Collaborating with AI

Maya (Fig. 4). The cases served two purposes: (1) to illustrate different patterns of reflective practices and SRL, and (2) to investigate how AI-generated ideas were taken up in participants' design sketches.

Eli: Iterative Evaluation and Reflection

Eli's dominant strategy (Table 3; panel A, Fig. 4) was to iteratively *evaluate* several elements in each AI-generated responses, *reflect* on how the elements aligned with her design ideas, and brainstormed solutions that combined the participant's insights with the AI's suggestions (*move*, *tactics*). During the individual brainstorming without ChatGPT, Eli identified a key problem with the learning management system (LMS): the lack of customizable calendars to keep track of deadlines across classes. Her session with ChatGPT included several questions to narrow down the design space for the calendar feature:

1. Identifying user struggles ("What are the problems that Canvas users run into with the calendar events?").
2. Finding best design practices ("What are some suggestions to limit human errors?").
3. Ideating ("Is there a way to connect the calendar events with the syllabus?").
4. Critiquing design ("Critique this update to Canvas calendar: individual teacher events have the ability for each student to create a personal due date").

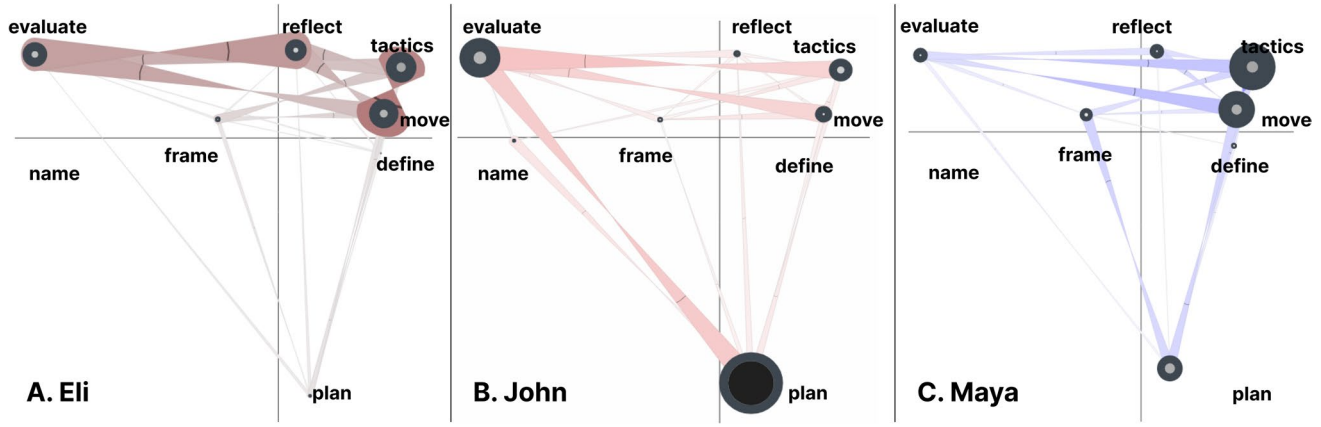


Fig. 4 Ordered networks of Eli (**A**), John (**B**), and Maya (**C**). *Notes*. Eli and John: higher-scoring group (red), and Maya: lower-scoring group (blue)

ChatGPT generally created a list of features in response to these questions (Table 3). Eli evaluated each of the response by highlighting the elements that stood out and considered how these elements might improve the design. For example, she stated: "My train of thought with this is it would be cool, you could take that event and set a personal due date [*AI-generated idea*]. And then, have it locked where it can't go past the due date of the teachers [*Eli's elaboration*]".

We next examined how Eli *highlighted* AI-generated ideas, *elaborated on* how feasible the ideas were within the design space, and *integrated* them into the final design sketches (Supplementary Information A). Overall, Eli considered 15 ideas that ChatGPT suggested and elaborated on eight of those. Out of the eight, she incorporated four into the design sketches. These interaction patterns reflected extensive uses of ChatGPT for idea generation and critique. In the debrief following the interactions with ChatGPT, Eli reflected that the AI tool presented "wider perspectives" and "pulled from other reviews and experiences of people using learning management systems, to critique the gaps in designers' thinking". Eli's sketches reflected a high level of human-AI idea incorporation, incorporating several views of personal calendars and event description to reduce system complexity. Eli also received a high score for solution detailedness, as she accounted for ChatGPT's critique for system complexity in the design.

John: Planning and Evaluation to Elaborate on AI's Ideas

Meanwhile, John's session was marked by iterative combinations of *planning*, *evaluating*, and making design *moves* and *tactics* (panel B; Fig. 4). He gave clear role-play definitions for the AI in the beginning, "Pretend that you are a UX/UI designer with 10 + years of experience", and then asked the AI to walk him through each step of the design process. Consider John's thought process at the beginning of the brainstorming session.

> It's all in that prompt engineering, right? One of the things I do a lot with ChatGPT is that role-play idea […] One thing we could do is a prompt, for the duration of this conversation, you will act as a UX/UI designer with 10 plus years of experience. […] Give me a design outline that highlights our user base. [...]

In this excerpt, we observed intentional framing of the AI's role. John framed the task as iterations of asking the AI to role-play ("as a UX/UI designer") and made explicit his workflow of evaluating the responses and revising prompts. The framing showcased metacognitive awareness of how to approach AI interactions. It set the tone for the rest of John's brainstorming session, when he engaged in recurring sequences of *planning*, *tactics* (prompt generation and summarizing), and *evaluation* to adjust prompts. For instance, when ChatGPT stated "As a text-based AI, I'm unable to provide visual mockups directly" to John's request for a mockup of the outline, John stopped the response generation midway to rearticulate his prompt (Table 4).

Based on the outline that ChatGPT created, John used subsequent prompts to move through design steps (identifying user groups, examining user needs, and ideating possible solutions). John *highlighted* seven of AI's proposed ideas. Out of those, he *elaborated* on four and *integrated* two into the design sketch. Specifically, John took two of the AI's suggestions (progress tracking; tagging system) and added his own twists, e.g., "I put a little filter icon (based on the tags), like you can organize the students by like who hasn't progressed quite as far". John's intentional framing of AI's roles was evident in his debrief. He stated that although ChatGPT was "more useful than expected", he would change the prompts to clarify AI's capacities in future iterations.

Table 4 John's prompts, AI responses, and think-aloud with ChatGPT

Prompt to AI	As a UX/UI with 10 years of experience, create a. mockup of step 1 [of your outline]
AI responses	As a text-based AI, I'm unable to provide visual mockups directly. However, I can describe the elements and content you may include in a mockup […] 1. User Research Mockup: Header: include the project title … Introduction: Provide an overview of the research objectives and explain the importance of gathering user insights … Methodology: Describe the research methods employed …
Think-aloud	And stop generating that and then I want to go back up to that prompt that we've done and let's edit that prompt
Prompt to AI	Create an example of step 1
AI responses	As a text-based AI, I can provide you with an example outline for Step 1 of the user research phase User Research Plan – Step 1: Gathering User Insights 1. Introduction: Project title: Canvas Learning Management System Redesign Objective: Gather user insights to understand the pain points … 2. Research Methods: Interviews: one-on-one interviews with a diverse group of students and instructors Surveys: Distribute online surveys to a larger sample of Canvas users Usability testing […]
Think-aloud	It's focused it's even given us some pretty decent research questions. […] I will actually go and create step 1 myself, but this gives me a good guideline. I'd scroll back up to see what steps it broke it down to …

Maya: Moving and Tactics

Being new to ChatGPT, Maya relied on *moving* and *tactics* as her dominant strategies (large node sizes for *move* and *tactics*, panel C, Fig. 4). Her prompts aimed to gather information about the design space, with less planning and evaluation, compared to the other two participants (Table 5). In total, Maya *highlighted* six of AI's ideas, *elaborated on* three of those by articulating how the ideas aligned with students' experience with the LMS, and *integrated* one idea (progress tracking) into the design sketch. Her sketch reads: "I would call it a self-student tracking … Task management stuff and time management. You could have personal learning plans." This description mostly repeats the AI's ideas, without much elaboration. In her debrief, Maya found the interactions with ChatGPT "intuitive for question asking". She suggested adding example questions that designers could ask the AI to jumpstart the process.

Table 5 Maya's prompts, AI responses, and think-aloud with ChatGPT

Think-aloud	That's a lot of features. Is it on there on Canvas? I feel like some should be on there I don't think it's necessary to put all of it down. Obviously, the grading we would need And progress tracking would be really good. Although there is a gradebook, like you get to see your percentage grade, but I feel like with the progress tracking tool, you can see how many assignments you've completed …
Prompt to AI	What elements from above are most important to a student?
AI response	The importance of elements in an online course can vary … However, some commonly important elements for students in an online course are: 1. Course Material: The quality and comprehensiveness of the course material are crucial for effective learning 2. Assignments: Assignments help students apply what they've learned and reinforce their understanding. […] 3. Progress tracking: Progress tracking helps students monitor their advancement and stay organized. Clear indicators of completion percentages, grades, or progress bars …
Think-aloud	I feel like it's everything I actually said. That's pretty cool Could I ask it more insight, kind of more in-depth framing
Prompt to AI	Tell me more in-depth information about progress tracking
AI response	Progress tracking in an online course involves various tools and features that allow students to monitor and assess their advancement. Here is a more in-depth look: 1. Completion Tracking … to show students how much of the course they have completed 2. Grade Tracking … track their grades throughout the course 3. Feedback and corrections […]
Think-aloud	Oh, that's cool. I wish we had that

Discussion

Our study explored how students and professionals engage in reflective design practices and SRL when utilizing GenAI. We focus on how emerging AI technologies can support design thinking as a fundamental process in STEM disciplines (T. Li & Zhan, 2022; Razzouk & Shute, 2012). For RQ1 about patterns of interacting with GenAI, we found that *moving* and *reflecting* were the most frequent reflective design practices. Participants frequently engaged in SRL such as executing *tactics* (e.g., summarizing, brainstorming, elaborating), *planning*, and *evaluation*. We linked the reflective practices and SRL to the quality of design artifacts (RQ2). The ONA revealed that participants in the higher-scoring group engaged in more *evaluation* in conjunction with *reflection* to reframe design solutions, compared to those in the lower-scoring group. Our case studies illustrate that collaboration with an AI tool can augment participants' decision-making to refine design ideas in various ways (D. Wang et al., 2019). Eli and John followed efficient design steps and build on the suggested ideas, while Maya found a design feature she had not previously considered. These findings illustrate the utility of the AI tool to help outline the design steps, ideate a range of features, and critique design ideas (Chung et al., 2022; Jung & Cho, 2022; Yang et al., 2022). Results also illuminate how learners need to employ new mechanisms to plan, monitor, evaluate, and reflect on learning processes (Chang et al., 2023).

Reflective Practices and Self-Regulated Learning in AI-integrated Tasks

Findings suggest that individuals who scored higher in their design sketches showed engagement in more sophisticated and multifaceted reflective design practices and SRL (Molenaar & Wise, 2022; Winne & Hadwin, 1998). Our qualitative excerpts illustrated different approaches. Eli and John participated in iterative planning and evaluation of the AI's responses, in combination with reflection on the design context and their design visions. Using the AI tool to gather information and generate ideas may spur novel or unexpected details about the design problems (Jung & Cho, 2022). These details may invite reflection and subsequent moves to expand the design solutions (Stompff et al., 2016).

The proclivity for more advanced SRL activities among the higher-scoring group suggests more refined metacognitive awareness (Azevedo et al., 2010). Given the vast amount of information and feedback AI tools can generate (Rudolph et al., 2023), learners need robust self-regulatory skills to navigate, filter, and integrate the provided information effectively (X. Wang et al., 2023). Learners continuously evaluate and recalibrate their learning approaches in response to feedback from both the learning environments and the technologies (Zimmerman, 2013). Our finding also supports prior research (Greene & Azevedo, 2007) that the complexity of SRL could serve as indicators of academic achievement, especially in technologically advanced learning settings. While AI tools can adapt to learners' needs to some extent, learners should actively engage with materials, seek clarification when needed, and be agile and adaptive in the SRL processes. Without SRL and reflective practices, learners might become passive recipients of information and overly rely on AI recommendations (Qadir, 2023; X. Wang et al., 2023).

Implications for Education: Embedding SRL and Reflection in Human-AI Interaction

Our study contributes to the discussion on the implications of AI in education, particularly in leveraging AI to ideate with learners and support knowledge refinement. GenAI that is publicly accessible has garnered much excitement for their potential to transform education (Dwivedi et al., 2023; Rudolph et al., 2023). These tools can respond to complex questions in natural language and make information readily available to a wide audience. This increased access, in theory, should improve learning and level the playing field for all learners. However, our results suggest that the technology alone cannot ensure effective learning. While all participants were enthusiastic about the prospect of GenAI and posed questions to ChatGPT with ease, not everyone engaged in reflective design practices and iteratively evaluated the AI's responses to improve design ideas. These interaction patterns might relate to participants' familiarity with ChatGPT and perceptions of how it could be used for design (Shoufan, 2023). Designers might hesitate to use GenAI for idea generation and critique, out of consideration that AI might reduce overall creativity (Doshi & Hauser, 2024) or replace, rather than augment creativity (Lu et al., 2022). Further, individuals possess different level of reflective practices and SRL skills (Mosely et al., 2018; Tang et al., 2012). Enhancing familiarity with AI capacities and knowledge about how to create, regulate, and apply AI-generated information might support more reflective engagement with the technology.

Findings offer educators valuable insights into the role of SRL and reflective practices in design thinking and other STEM contexts (Karimi et al., 2020; Relmasira et al., 2023; Tholander & Jonsson, 2023). When interacting with AI tools, learners need to develop robust strategies to evaluate AI-generated information and feedback (Järvelä et al., 2023). This evaluation process is not just about understanding the content. It is also about critically assessing the information's

relevance, accuracy, and applicability to the tasks at hand (Rudolph et al., 2023). Educators can facilitate these evaluative skills, by emphasizing SRL in AI-integrated learning environments. They can model different AI roles (e.g., as a partner to seek information in Maya's case or an idea generator and evaluator in Eli's and John's cases) and when and how to employ different SRL activities. Educators can also pose reflective questions that encourage learners to self-initiate feedback about human-AI's joint progress (Van Laer & Elen, 2017).

Our research prompts questions for future inquiries. For instance, what are the design principles to facilitate reflective practices and complex SRL in AI-integrated learning? How can educators scaffold learning experiences to nurture SRL, considering learners' familiarity with the tools and learning experiences? Exploring these avenues will be instrumental in harnessing the full potential of AI in fostering robust SRL across learning settings.

Implications for Learning Analytics: Applying ONA

Our study demonstrates the utility of applying ONA to examine multifaceted human-AI collaboration. Researchers have emphasized the need to move beyond frequency-based analyses, to examine the interrelations between SRL activities and their progression over time (Fan et al., 2023; Saint et al., 2021). The ONA results provide important insights into the interconnectedness, direction, and sequences of design practices and SRL. Such information is critical to understand the flow of learning process (Brohinsky et al., 2021). For instance, a pattern where evaluation is frequently followed by reflection suggests an iterative and reflective approach to AI-integrated learning. Additionally, we found higher numbers of self-loops of evaluation and reflection in the higher-scoring group, compared to repeated uses of tactics in the lower-scoring group. Information about recurring patterns can signal involvement in more complex SRL as they unfold.

Limitations and Future Research

Findings should be considered in light of several limitations. First, we used the readily available ChatGPT to explore how participants engaged with the tool off-the-shelf. This setting constrained participants' interactions to question-answering (as of May–June 2023), without the AI actively asking follow-up questions or utilizing shared regulation to establish awareness of participants' goals. Future research can fine-tune LLMs and explicitly frame the tool as a facilitator of SRL and design thinking. Such framing allows for investigating other regulation processes like co-regulation and socially shared regulation (Järvelä et al., 2023).

Second, the research is exploratory with a small, self-selected sample of participants who were already interested in applying GenAI in design contexts. The variability in participants' reflective practices and SRL skills might affect the generalizability of the results. Future research could incorporate a larger and more diverse sample, control for differing skill levels, and conduct more in-depth analyses of the relation between familiarity with GenAI, reflective practices and SRL, and interactions with the tools. Additionally, future work can explore educational interventions. For example, researchers can examine how SRL scaffolds can impact learning processes in collaborating with AI tools, as well as the design principles and analytics to measure and facilitate SRL and design practices in AI-integrated settings.

Finally, we build on prior research to conceptualize reflective practices, SRL, and human-AI collaboration. Researchers can explore these concepts from other theoretical perspectives, to uncover new insights into how humans and AI might interact productively. Building on the different uses from the case studies, we invite follow-up research on the different roles that AI can play in design contexts, for instance, as an idea generator, critique, or validator.

Conclusion

We explore how individuals brainstormed with a GenAI tool to support design thinking. We leverage ONA to provide more nuanced understanding of the sequences and co-occurrences of SRL and reflective design practices. Findings highlight the role of reflective practices and SRL in AI-integrated settings. While AI technologies can provide information on demand, learners need to set goals, plan for human-AI interaction, and critically evaluate and reflect on AI's responses to adjust strategies. Our research raises important questions for future inquiry, to investigate ways to evaluate unfolding SRL and reflective practices and examine the impact of scaffolds in AI-integrated learning.

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Data Availability Data are available from the authors upon reasonable request.

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