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Shall We Play a Game? Distributed Games with a Generative AI Player

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Abstract: The prevalence of generative AI tools – especially large language models that enable human-like conversation – provides an opportunity to study how human learners interact with AI as collaborative ideators in the learning process. We expand the framework of distributed games (which initially focused on epistemic games of discovery as distributed processes) to investigate learner interaction with generative AI in design tasks. Through a comparative case study of two undergraduates using a generative AI tool in design tasks, we illustrate different ways in which learners orient themselves to the elements of the game (task, form, other players, etc.) and the corresponding complexity of the game played. We discuss implications for the design of learning environments that facilitate interaction with AI tools in distributed creative tasks.

Introduction

Advances in generative artificial intelligence, particularly large language models that can generate human-like, conversational text, have promise for supporting teaching and learning (Kasneci et al., 2023). To promote learning, it is critical to examine how learners approach tasks with AI tools. In this study, we explore the way different participants interact with a tool in a distributed design game – a deliberately collective effort to complete a design task. Participants were given a design task within a User Experience Design context and engaged in a brainstorming session with OpenAI's ChatGPT to develop and refine design ideas. We present two case studies of undergraduate participants. We identify the participants' different framings of the task and the role of the AI tool and present narratives to show connections between the framings, the design games, and the produced design sketches. The following question guides our research: **How do designers-in-training orient themselves to a design task with a generative AI tool?** Insights from this research have practical implications for guiding students to interact with AI systems in educational contexts.

Theoretical framework

The model of distributed games focuses on collective activity. We expand an existing framework (*epistemic games*) to describe another type of distributed game (*design games*), in which the goal is to generate a design.

Distributed games

The conceptualization of knowledge construction as an epistemic game guided by an epistemic form has been in use for several decades (Collins & Ferguson, 1993). This framework visualizes knowledge construction as the result of a scholar making *moves* in a *game*, which are made to fill out a particular template – for example, by filling in the rows of a list. Recent work has expanded this conceptualization with the added lens of distributed cognition (Hutchins, 2008) into a theory of *distributed epistemic games* (Matthews & Swanson, 2023; Matthews, Nguyen, & Swanson, 2023). Distributed cognition adds the importance of other elements in the thinking environment - including tools, artifacts, and other individuals - to the thinking that takes place. In a distributed game, the use of forms with moves made by players persists. The difference is that multiple players are playing the game simultaneously, often filling out multiple forms and creating *artifacts* as repositories of the knowledge generated by the game (*ibid*). Initial work in the distributed game framework has focused on a game which was played exclusively by human players (*ibid*).

In this paper, we expand previous work in two key ways. The first is that we look at games which involve the creation of a *design artifact*. The second is that we look at distributed games including an AI player.

AI players

Advances in AI, including development in large language models that enable conversational interfaces in the form of generative LLMs, have made it possible to position AI tools as collaborators in the design process (Nguyen & Hayward, 2024; Wang et al., 2020). These tools can not only generate novel ideas, but also engage in idea co-creation with human designers to continuously improve upon the design (Davis et al., 2015; Simeone, Mantelli, and Adamo, 2022). While promising, these tools can also be challenging to navigate, as designers need to articulate their goals, understand how to approach the tools, and continually assess the AI's outputs (Gmeiner et al., 2023). Thus, scholars have turned to educational research in human-human collaboration to inform the design of human-AI collaboration (Holstein et al., 2020; Schelble et al., 2022). For example, Bansal et al. (2019) investigated how to facilitate shared mental models, or understanding of the task and the AI's capacity, to adapt how human actors collaborate with the tools. Our study contributes to this emerging research through the lens of distributed games. Here, the AI tools can be positioned as another player contributing to the creation of design artifacts.

Orientation

Orientation plays an important role in the framework. The way players orient themselves to the game and other players impacts the moves that they make. We differentiate this notion of orientation from concepts like task orientation, which focuses on goal-driven learning activities (Pintrich, 2004), and note the similarities between orientation and the different ways in which individuals engage with AI during design tasks (Simeone, Mantelli, and Adamo, 2022). In our definition, a player's orientation within a distributed game reflects their prior experience, expertise, and perspective.

A player's orientation impacts the objects of a player's *attention* - what they attend to such as the environment, tools, and players - as well as their *interpretation* - how they make sense of their objects of attention. Orientation also includes a player's *familiarity* with the objects of attention.

Methods

Study setting and participants

This study included 17 designers with different design expertise in Summer 2023 (Institutional IRB #13497). Participants included seven professionals in UX/UI and instructional design, four graduate students, and six undergraduate students in a design program in the Intermountain West region of the United States. Participants were recruited via a flier disseminated through the program's listserv for current students and alumni, to invite individuals interested in using generative AI in design contexts. Participants received a $10 gift card for completing the interview.

The interviews were conducted via video conference call and lasted 45 minutes on average. They were video and audio-recorded and transcribed automatically by the video conferencing software. During the interviews, participants received a task to redesign the navigation of a learning management system to enhance the user experience of instructors and students. Participants first engaged in individual brainstorming (10 minutes) to gain familiarity with the design space (e.g., identifying key users, researching user needs, brainstorming design solutions). They next used a free generative LLM tool to refine their design ideas (10-15 minutes). The chat interactions with the AI were screenshared, and interviewers prompted participants to think aloud with questions such as "Why did you ask [the AI] that question?", or "What do you think about the AI's response?" Participants had 5-7 minutes to sketch design solutions on paper, based on their individual brainstorming and interactions with the LLM. They verbally presented the sketches and then took photos of the sketches and emailed them to the interviewers. The interviews ended with a debriefing session, where participants outlined what they liked and wanted to improve about the interaction.

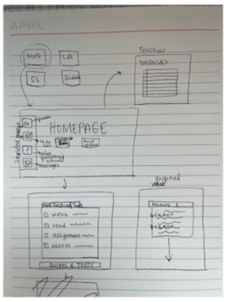
Data sources

Our analysis drew from multiple data sources. To understand the *design moves* that participants engaged in within the distributed design game, we focused on the video recordings and interview transcripts. We specifically examined the human participant's utterances *within* human-AI exchanges (both think-aloud and prompts). Each utterance, prompt, and response was coded as a move in the game.

Additionally, we evaluated the *quality of the design sketches* that participants developed, following their brainstorming with the generative LLM. The rubric (shown in Figure 1) comprised four categories on a scale of 0-5: usefulness, novelty, elaboration, and incorporation of human and AI ideas. The first two measures were linked to how design researchers have defined creativity (Runco & Jaeger, 2012). We added a measure for elaboration, to explore how participants specified details for their design (Dally et al., 2016). Finally, the human-AI idea incorporation category indicated the extent to which the design sketches incorporated both players' ideas, as a marker of design product co-construction. We summed up the scores per participant for the categories: $M = 10.58$; $SD = 2.49$ (possible maximum score of 20; range of 6-15).

Figure 1
Design sketch rubric

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).

Analysis

Case selection

In addressing our research question, we focus this paper on a comparison between two undergraduate students or *designers-in-training*: John and Barbara (pseudonyms). The two participants had similar schooling experiences, as both were entering their senior years in their Design undergraduate degree. They were selected through the extreme sampling method based on the participant scores on the design sketch rubric (John: design score = 13/20; Barbara: design score = 9/20). The participants represented the highest and lowest scores among the undergraduate participants. When asked about their prior experiences with the AI (generative LLM), John brought up personal use such as creative writing & brainstorming, while Barbara had not used or heard of this generative LLM before the interview. Both participants spent roughly the same amount of time with the AI (~12 minutes).

Analytic procedures

We answered our research question in three steps. First, we developed a codebook for participants' design moves through a grounded theory approach (Charmaz, 2006). The analysis unit was at the sentence level and we focused on participants' utterances during the section of the interview in which they were creating *prompts* for the generative AI. At the beginning of the process, the first author identified various design moves (see Table 1) within the transcript data. These codes were then refined by all authors in three discussion rounds. Next, the first and second authors collaboratively coded both transcripts, using a process of social moderation to discuss and resolve any disagreement (Frederiksen et al., 1998). Next, we wrote up the case narratives for the two selected participants which included a description of the sequences of the design moves during the brainstorming sessions. We followed this with a cross-case comparison to illustrate how participants approached the task and the collaboration with the AI tool.

Table 1
Codebook of design moves

Move	Definition	Example from transcript
Orient to task	Clarify and get information about the task and state perceptions of the AI tool	What do you mean? So, we're attempting to redesign …
Find approach	Find approaches to working with the AI	We can give it the prompt for what we want it to do [...] so now it will act as a UX/UI designer.
Prompt	Prompt or refine prompts to the AI	Can we ask, is the system useful to students?
Ideate	Brainstorm ideas independently or with AI	I feel like a progress tracking tool would be really good.
Review	Read and review AI's responses for their accuracy and helpfulness	I feel like it's actually everything I said. That's pretty cool.
Reflect	Reflect on the design space, drawing from personal experience or design feasibility.	It's nice to see as a student, a good tracking point.

Findings

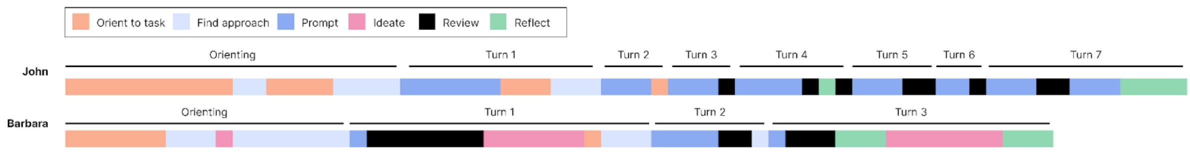
Session overview

We first present an overview of the brainstorming sessions with the generative LLM AI based on coding participants' think-aloud utterances. We found iterations of *task orientation, finding approach*, and *prompting* in John's session. Meanwhile, Barbara's session was characterized by long periods of *finding approaches*. While participants spent the same amount of time with the AI, John sent seven prompts to the AI, while Barbara sent three prompts.

We delve into these patterns in more detail when analyzing the prompts that participants posed to the AI and how they evaluated the responses. Specifically, we found two macro-level games that participants were playing with the AI tool: *guided roleplay* (John) and *defining the design problem* (Barbara).

Within a distributed game framework, we use *turns* to indicate cycles where *players* make *moves* in sequence. A *player* may make multiple *moves* in a single *turn*. Each *turn* can be a level of analysis, with one or many *turns* comprising a micro-level *game* within the macro-level *game*. In this section, we review the turns of each player's game, with each turn marking a prompt that participants submitted to the AI. A turn can involve multiple moves, such as finding approaches before submitting a prompt, or reviewing response following prompt submission. Each turn is numbered and given a descriptive (and bolded) name, and the moves (as presented in Table 1 above) are also bolded. As in the rest of the paper, we continue to use italics for emphasis.

Figure 2.
Overview of the brainstorming sessions



John's distributed design game: Guided roleplay

John's game is marked by a sequence of *finding approaches*, *prompting*, and *reviewing* (see Figure 2). In this section, we present a narrative of the specific moves made during his game play centered on the prompts that he sent. We characterized this sequence of moves, at a macro-level, as fitting patterns of a design game of *guided roleplay*. Here, John specified both role and goal for the AI player, and then moved through a sequence of micro-games, including *setting up roles* (turns 1, 2), *decomposition of design steps* (turns 2-5), *making lists of design challenges* (turn 6), and *compare/contrast* solutions in a problem-centered analysis (turn 7).

Turn 1. Defining AI role & checking for understanding. Prior to sending the first prompt, John spent several utterances articulating his *perceptions of the tool* and **finding [his] approach**. He stated: "So there are a couple of ways we can approach it, and it's all in that prompt engineering, right? … the things I do a lot with Chat GPT, GPT is essentially like that role play idea, like I tell it you're going to act as this kind of person with this kind of knowledge." With this framing, John's first **prompt** to the AI aimed at *defining roles and checking for understanding***.** The prompt stated: "For the duration of this conversation, *you'll act as a UX/UI designer with 10+ years of experience*. I'll approach you with a redesign project, and you'll give me a design outline that highlights our user base, what features need to be reworked, and a list of potential solutions. Do you understand?" The AI responded: "Yes, I understand. As a UX/UI designer with 10+ years of experience, I can assist you with your redesign project. Please provide me with the details of the project, including your user base, the features that need to be reworked, and any specific goals or challenges you'd like to address."

Turn 2. Defining the goal for the conversation. John then moved on to his second **prompt** to *define the goal of the conversation* and generate a list of the design steps. He specified: "We are *attempting to redesign the Canvas learning management system*, so that it'll be more user-friendly … We need to figure out what features are less user-friendly and identify solutions that will help Canvas be more competitive in the coming years." The AI player responded with an outline of the design approach, specifying each step such as User Research, Defining User Personas, and Feature Analysis.

Turn 3. Requesting a mockup of a design step. John's next **prompt**, after **reviewing** the previous move, was to get more details after the "pretty generic response," and *request a mockup of the user research section*. The AI responded to John's next prompt: "As a text-based AI, I'm unable to provide visual mockups directly." The AI then listed content that the first User Research step might include (e.g., header, introduction, methodology). John **reviewed** the answer and remarked, "Not quite what I was looking for, I think the word mockup threw it off." He stopped the AI mid-response and moved to the next prompt.

Turn 4. Adjusting the prompt. John then edited **prompt #3** to request an example of the design step. The AI's response to this included an outline with several elements. For instance, the AI suggested asking: "What are the major pain points or frustrations experienced while using the Canvas system." John **reviewed** the response. "This is a lot better. It's a bit more focused and has given us some pretty decent research questions" and **reflected** on its utility to the design process. "I couldn't just run with this, I'd have to go and create step one myself, but this gives me a good guideline." He then **reviewed** the AI's prior response to prompt #1 (listing the design steps) and continued with his next prompt.

Turn 5. Reminding the AI of the role; asking for elaboration on the next design step. John moved to the next step of the design process, Defining User Personas, based on the AI's initial outline. He **prompted**: "*Remembering that you are a UX/UI designer with 10+ years of experience*, complete step 2 of the outline that you provided, using hypothetical users that represent the Canvas system." In response, the AI created two personas: Emily, a college student, and Professor Mark, an instructor, along with the background, goals, behaviors, and pain points (i.e., challenges/frustrations with the interface) for each user. It identified a challenge for Emily as "difficulty locating specific course materials or assignments," while it suggested that Mark might find the "process for uploading and organizing course materials cumbersome." In **reviewing** the response, John made connections with the ideas he had developed initially in the individual brainstorming session, "the pain points this is highlighting are pretty similar to the outline that I had gone through." At this point John moved on to generating design solutions.

Turn 6. Requesting a list of solutions to the pain points of each persona. John continued building on previous exchanges with the AI, and **prompted**, "As *a UX/UI designer of 10+ years of experience*, take those user personas and generate 4 to 5 solutions per user for their pain points." In turn, the AI generated several solutions to address Emily's and Mark's (the hypothetical personas) challenges with LMS navigation. It proposed developing "enhanced course material organization," including "a tagging or search functionality," to "make it easier for Emily to locate specific resources." In **reviewing** the AI's answer, John exclaimed "Wow, like it's good. It's not detailed, but I'm still kind of impressed." He then strategized with the prompt to gain more details into the solution.

Turn 7. Requesting detail for design solutions. John posed a **prompt** to the AI to "give me some example implementation for solution 1." The AI responded: "Certainly, here are some example implementations for solution 1, which focuses on enhancing course material organization," and listed solutions such as "visual folder structure," "tagging system," and "personalized favorites or bookmarks." John **reviewed** the answer and noted what stood out to him, e.g., "A tagging feature, under number 2. I kind of like that. I think that could potentially simplify things. I want to look into that." John then dived into **ideating** and **reflecting** on the design feasibility for several utterances. He concluded the brainstorming session with a reflection note, "This is a really good way to get a good general chunk of ideas that you can kind of start working with."

John's process stood out to us, as he was engaging with the AI in a game of guided roleplay, where the AI was given not only tasks, but a character (role) to *play* for the duration of the *game*. This role was defined at the beginning of the conversation, and John reminded the AI of the role in several prompts. Additionally, John moved through multiple requests to play different mini-games within the larger macro design game of guided roleplay, such as *generating lists, requesting a mockup*, and then *creating design solutions*. Following the session, John's design sketches integrated several ideas from his conversation with the AI, including a tag system incorporated into both student-facing and instructor-facing interfaces.

Barbara's distributed design dame: Defining the design problem space

Barbara's macro-level game is a search for a good approach to engage with the task and AI player. Early in the AI-brainstorming session, she worked with the facilitator to review a sample prompt to better understand how the interface works. While John was able to engage with the AI tool independently, Barbara turned to the interviewer in the beginning to request reminders about the task and guidance about how to create a prompt. Barbara's prompts followed a consistent pattern of *list-making* throughout the macro-game of *defining the problem space*.

Turn 1. Requesting a list of common features of an online course. Following several utterances to **orient to the task** and **find approaches** to working with the LLM (e.g., "I don't know how to put that in words"), Barbara started with a basic **prompt** of "What are the common stuff in an online course?" She carefully **reviewed** the AI's response in several utterances to call out the ideas that she liked, and then **ideated** based on the AI-generated features. As an example, she noted that "The progress tracking tool would be really good for a student to see how far along." Not sure what to ask next, she needed reminders from the interviewer about the task (the interviewer prompted: "how might you use those components for your redesign?"). Barbara went through a few utterances to **find approaches** for her next prompt and decided to focus on students as potential users.

Turn 2. Requesting a list of features most helpful for students. Barbara **prompted**, "What helps the students, I mean, what elements from above are most important to a student?" In response, the AI highlighted several features such as course materials, assignments, and instructor support. Barbara **reviewed** the response and remarked that "it is everything I actually said. That's pretty cool." She again took a moment to **find approaches** and asked the interviewer if she could get "more insight, kind of more in depth information."

Turn 3. Requesting information about a specific design feature. The interviewer encouraged Barbara to articulate the **prompt**, which she stated as "Tell me more in-depth information about progress tracking." Here, we observe that the participant narrowed down her design focus to a specific feature and used the tool to request information. In response, the AI provided several features for progress tracking, including completion tracking, grade tracking, and self-assessment. Upon **reviewing** the response, Barbara noted that "that's really cool. I wish we kinda had that on Canvas." She was particularly interested in student-facing features (e.g., time management tools, assignment tracking), and engaged in several utterances of **reviewing** and **reflecting** on them. She noted, "students have hard times with those [time management]. It's nice to see as a student, a good little tracking point." She continued pursuing these ideas in **ideation**, with features such as personal learning plans, to-do list, and milestones, and **reflected** on how these designs might be useful from a student's perspective.

Barbara spent her game seeking information in various forms. She started very broadly—*orienting to online courses*—and then focused on a specific group of users. For this group, she *investigated a list of features* and then *drilled down for more information about a specific feature*. As the game progressed, she became noticeably more comfortable with both the task and the AI player. We characterized her strategies as finding approaches to define the design space and orient to the AI tool. While she was able to incorporate the progress tracking idea in her final design sketch, her solution did not have as many details as John's, and instead just repeated the AI's feature descriptions.

Discussion

This work adds two key features to the larger framework of a distributed game. These are the importance of *player orientation* and a way of measuring the *complexity of the game*.

Orientation

Orientation to the AI showed up for both players (John & Barbara) in different ways over the course of the game. The participants oriented very differently to the AI player, with Barbara spending time building familiarity, while John started with prior experience. These different orientations changed the roles that the participants and AI played. For example, early in the game, John carefully *defined (the) role of the AI* and *checked for understanding*. He started with a very clear role and task and used these to guide the AI through the game. During the game, John maintained his role as the guide in a macro-game of role-play. In comparison, Barbara was not as familiar with the AI, and so needed to spend the time orienting herself to both the AI player and the task. She oriented to the AI as a *source of facts*, whereas John explicitly assigned a role and oriented to it as a *thinking partner*. We note *role definition* as a step which is potentially unique to a *distributed* game.

Complexity of the game

John iterated quickly through turns within the macro-game, with three of his seven turns consisting of a quick **prompt-review** process. Additionally, John moved through six micro-games, (1) *role definition,* (2) *task definition,* (3) *requesting a mockup* (4) *listing (design) challenges*, (5) *compare/contrast,* and (6) *creating design solutions*. Both the quick iterations and the use of multiple different micro-games signified a more complex macro-game.

Meanwhile, Barbara started the game with much less familiarity & comfort, so she relied on the facilitator during the early stages of the game. As the game progressed, she became more familiar with the AI and focused her interactions there. Even with her increased familiarity, Barbara primarily engaged in only *list-making* micro-games, adding a *create design solutions* micro-game at the end as well. She also took more of the game time to **review, orient,** and **find approaches** to working with the AI player. Looking at her macro-game as a whole, it is clear that it took the additional time and effort for Barbara to become more familiar with the AI player. Because of the slower iterative process and the focus on a specific type of micro-game, Barbara played a less complex macro-game.

Implications

Our findings about the different ways the participants oriented themselves to the design task and the AI, as well as the resulting complexity of the games that they played, have implications for educational practice. Specifically, we note the importance of additional support in task structure and facilitation to help students orient themselves to an AI-integrated, distributed game. We observe that guidance from the facilitator helped Barbara get to the point where she could play more directly with the AI. As educators find ways to use and evaluate AI in instructional settings, it is helpful to see how guidance from a facilitator or task design may strengthen students' orientation.

Limitations and future work

There are some limitations with the current work. First, this study reported on short durations of interactions with the AI player, so we only observe the first stage of the design game (i.e., exploring the design space and ideating). Second, while we have conjectures about the role of orientation to the task from the cross-case analysis, we are not making definite claims. We encourage future work to investigate these conjectures further.

Additionally, future work with theoretical frameworks of distributed games, both *epistemic* and *design*, should include the AI (where present) as a player in the game. This inclusion should involve ways to describe AI *moves* within the game, as well as ways to describe the turns between human and AI players. This will allow the creation of descriptions for how AI players participate in distributed processes of both knowledge generation and design. Finally, researchers might evaluate whether the way players perceive/approach the AI can be guided by a teacher or trainer. It may be that this orientation is malleable and can be directed towards specific goals.

Conclusion

In this paper, we expand on the framework of distributed games as a collective *knowledge construction* process (Matthews & Swanson, 2023; Matthews, Nguyen, & Swanson, 2023). Players within a distributed *epistemic* game interact to collectively *create* knowledge. We expand the framework by adding a distributed *design* game as collective *creation* of design. We compare two player's games side-by-side, to examine different orientations to the game and game complexity. These differences give us a sample of the range in characteristics that is possible within a distributed game. Additionally, the analysis included an *AI player* as part of design creation. Our work illuminates the role of AI in augmenting participants' moves. Acknowledging the role that AI has in design and the way other (human) players interact with it is a key step in building a framework of distributed, AI-integrated processes of creativity.

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