Relational Dynamics in Human-AI Co-Creative Learning

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Abstract

Computational co-creativity research has advanced methods for designing and studying the collaboration between artificial intelligence (AI) and the user in creative artifact development. We want to understand better how co-creative systems can affect creative capacity development with a focus on the user's perceived relations with AI. In this study, we conducted an exploratory experiment in a virtual environment where a human and a machine agent engaged in collaborative problem-solving and learning activities using reinforcement learning. We analyzed the interview transcripts and video observation using constructivist grounded theory and found two significant dynamics between the human and machine agent, instrumental and relational, associated with the actions of interpsychological and intrapsychological creative learning. The relational dynamics have sub-dynamics like paternalistic, antagonistic, and empathetic. Every research participant had unique dynamics from the initial condition to the combination of these dynamics. We theorize a method of analyzing the human-AI dynamics in co-creative learning that can contribute to future research in co-creative systems.

Introduction

Computational co-creativity research provides promising ways to design systems that foster creative capacity in the users (Rezwana and Maher 2023; Kantosalo and Toivonen 2016; Lubart 2005). Unlike in a computer-supportive or fully autonomous computational creativity system, the user and artificial intelligence (AI) collaborate to develop creative artifacts in a co-creative system (Colton, de Mántaras, and Stock 2009; Karimi et al. 2018).). In a mixed-initiative model, the user and AI proactively take the lead in the creative process (Yannakakis, Liapis, and Alexopoulos 2014). Researchers have shown that these systems can enhance the user's creative capacity (Liapis et al. 2016). To expand on these works, the present study examines creative learning in co-creative systems from sociocultural creativity and learning science perspectives. In particular, the study seeks to develop a method to study the perception of the relationship between the user and AI, the outcome of which can be crucial from a creative education perspective and aims to identify the emergent categories of human-AI dynamics in co-creative learning. The present study describes the exploratory experiment in a virtual environment where a human and machine agent can take the initiative in collaborative problem-solving. During multiple iterations of collaborative activities, the study explores how human and machine agents learn from each other, using reinforcement and imitation learning.

The rest of the paper is organized as follows. First, we review the related works from computational creativity and discuss the sociocultural perspective of learning and activity theory in the context. Next, we describe the experimental system and the activities carried out in it, after which we present the data and analytical methods using constructivist grounded theory and video data analysis. In conclusion, we discuss the results of human-AI dynamics categories and theorize a conceptual model for future research analysis.

Background and Related Works

In studying the creative dynamics between humans and AI, the present study builds on the multidisciplinary research domain of computational creativity. The aims of the researchers are to develop autonomous systems that make a creative artifact and contribute to the broader understanding of creativity through making (Colton and Wiggins 2012; Veale and Cardoso 2019). Specifically in computational co-creativity research, studies often highlight the notion of initiative in human-AI collaboration (Deterding et al. 2017). At one end of the spectrum, the users take the lead in creative activities with computer support tools. At the other end, the autonomous creative system takes the initiative where the user observes. Between these two states is a mixed-initiative model in which both the user and AI are proactive in contributing to creative artifact development (Liapis, Smith, and Shaker 2016). Various initiatives can be categorized based on task, speaker, and outcome (Novick and Sutton 1997). In previous studies, researchers have applied these computer systems in creative domains, including game design (Larsson, Font, and Alvarez 2022; Kreminski et al. 2020), humor (Wen et al. 2015), drawing (Davis et al. 2015), music (Hoffman and Weinberg 2010) and storytelling (Alvarez, Font, and Togelius 2022). A diverse disciplinary method has been used for evaluating co-creative systems like protocol analysis, survey, observation, and semi-structured interviews (Jordanous 2012; Karimi et al. 2018). How co-creative systems impact the users' creative capacity has been researched broadly, including the user perception of various computational tools and specific creative capacities such as lateral thinking and creative emotive reasoning (Liapis et al. 2016). To expand on previous work, the present study examines the development of creativity capacity from a sociocultural perspective.

In addition, the present study is built upon the works of sociocultural creativity research. Sociocultural research over the past two decades has provided important information on creative learning (Sternberg and Lubart 1999; Lemmetty et al. 2021). In the domain of creativity studies, the researchers generally define creativity as a capacity to make something new and useful (Sternberg and Lubart 1999; Kaufman and Glăveanu 2019; Hennessey and Amabile 2010). The sociocultural approach examines factors such as actors, action, artifact, audience, and affordance in how society and cultural practices determine what is considered creative (Glăveanu 2013). The interaction among these factors influences both individual levels of creativity (small-c) and societal-level creativity (big-C) (Kozbelt, Beghetto, and Runco 2010). Specifically, the concept of 'creative learning' is understood as a series of interpsychological and intrapsychological actions that can lead to an insight or solution novel to oneself and the community (Beghetto 2016). One method of analyzing creative learning is activity theory, where an action is a unit of analysis that shows how a subject realizes its objective (Lemmetty et al. 2021; Sannino and Ellis 2013; Glaveanu, Ness, and de Saint Laurent 2020). The action can be as specific as talking, listening, and testing new strategies and concepts. These actions provide interaction among other factors in the activity systems, such as the tools, division of labor, and community. This aligns with the seminal theory of Zone of Proximal Development, which emphasizes the relationship in the learning environment where learners with varying levels of skills foster each other's growth (Vygotsky and Cole 1978). In parallel, there is research that focuses on the users' perception of AI in relational terms and concepts of anthropomorphism (Turkle et al. 2006; Złotowski et al. 2015; Epley, Waytz, and Cacioppo 2007). However, the perceived relations between humans and AI in co-creative learning have yet to be thoroughly studied. Therefore, the present study explores the relational dynamics between humans and AI in the context of activity system.

Study Methodology

For the present study, we created an experimental system in which AI is perceived as a relational artifact in creative learning activities (Lim et al. 2023). This experimental design allowed AI to progressively learn from the actions of human participants and the researchers to keep track of their learning in relation to creative capacity development.

The study included 15 human participants ranging in age from 18 to 40 (mean = 26.9, standard deviation = 5.3, female = 11). All the participants were either enrolled or worked at a graduate or undergraduate interdisciplinary design program at a university. Diverse ethnic backgrounds were self-identified (Asian, Caucasian, Hispanic, Indian, Middle Eastern, and Turkish). On a self-described scale of 1 to 5 (5 being the highest), most expressed general familiarity in virtual environments like gaming and joystick control (mean = 3.5, standard deviation = 0.9). They expressed general familiarity with AI (mean = 3.1, standard division =1.24) but not in specific topics like reinforcement learning (mean 1.6, standard deviation = 0.6).

Experimental System

We created an experimental system in a virtual environment where the machine agent can learn directly from the behavior of the human agent, who is the research participant. The system is co-creative because the objective is aligned between the human and machine agents with the incentives for collaboration in problem-solving. The system has components of the mixed-initiative model because both sides can take the initiative to solve the problem. While there is no explicit communication between the agents as in many other mixed-initiative models, the machine agent can augment human problem-solving with a divergent exploration of solution space iteratively (Deterding et al. 2017).

To foster co-creative learning, we made two specific design choices in the system. First, we gave the human and machine agents the same character design in the virtual space. Second, the human and machine agents were simultaneously learning how to solve the problem. The machine agent was trained between iterative rounds using the Unity ML-Agents Toolkit, which uses PyTorch-based algorithms to help train the agent using reinforcement learning, imitation learning, or other machine learning methods (Juliani et al. 2020; Sutton and Barto 2018). During the training, we conducted semi-structured interviews to capture the situational reflection of the human participants during their learning process.

Scenarios

We developed two scenarios with contrasting environments to create varying conditions for the emergent dynamics between humans and AI in co-creative learning.

Scenario 1 The first environment was a cubical ceilingless room with a wide pillar in the center. At the beginning of each round, the human and machine agents were instantiated at a random position on one side of the pillar. A blue sphere was positioned on the other side. We designed an environment where the solution was relatively easy for the human participant to achieve.

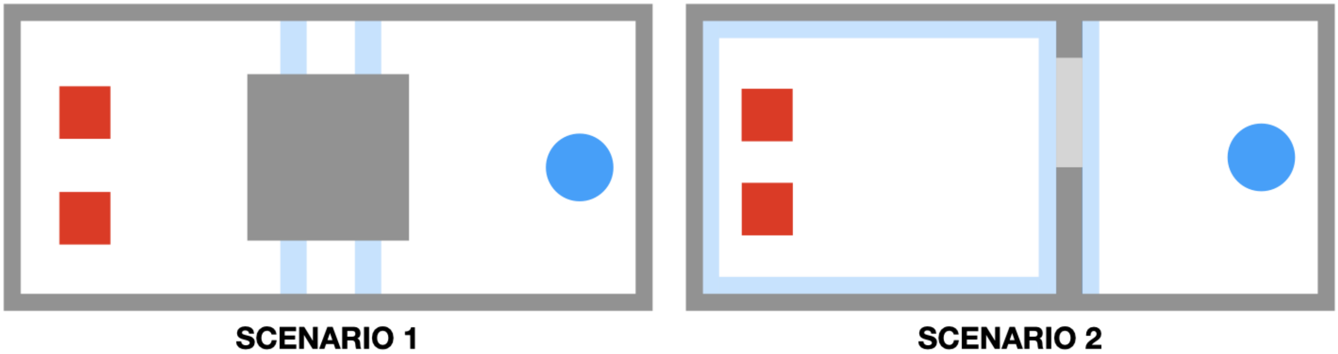

Figure 1: We developed different virtual environments for each experimental scenario. In both diagrams, the red boxes present the human and machine agents. The light blue lines are the checkpoints where the machine agent receives positive or negative rewards to incentivize its movement. The blue circle is the goal the agents were instructed to reach and earn points. In the Scenario 2 diagram, the light grey in the middle of the room represents the randomized hidden passage designed to increase the difficulty level for the human agent.

Scenario 2 The second environment was a larger cubical ceiling-less room with a smaller room attached along one side. At the beginning of each round, the human and machine agents were instantiated at a random position in the larger room. A blue sphere was positioned in the smaller room. The path to the smaller room was hidden by an invisible threshold, whose position was randomized every round along the wall between the large and small rooms. The human agent could move through the secret passage if they stumbled upon it. If the machine agent touched the passage, the door opened. We made the solution less intuitive to the human participant than in Scenario 1. The machine agent supposedly had an advantage because it learned the solution through random movements against the walls where the secret passage was hidden. The human agent tended to rely on visual identification of the goal before moving in any direction.

Experimental Activities

We explained the rules and navigation mechanics to the participants at the beginning of each experiment. Their goal was to hit the blue sphere and score as high as possible during each 2-minute round (The participant reached the goal = 1 point; the agent reached the goal = 10 points; the participant and agent reached the goal simultaneously = 20 points). We encouraged them to verbalize their thoughts during the round. We told them they and the machine agent could watch and learn from each other. After every two-minute round, the participant engaged in a 2-minute semi-structured interview to reflect their learning. Simultaneously, the agent was further trained to improve its policy. Afterward, the environment was refreshed with the newly trained machine agent for the next round. Each participant engaged in ten rounds (five rounds of two scenarios) that took approximately 60 minutes.

Reinforcement Learning

The experiment cycled between two modes: train mode, where the agent was trained in the environment without the participant present, and game mode, where the agent played with the participant. In train modes, the agent engaged in reinforcement learning, a machine learning method that trains a model to make increasingly optimal actions by rewarding it for desired outcomes. The following inputs, outputs, and rewards were defined to train the model through reinforcement learning:

Agent's Observations Observations from the environment served as input to the machine agent's model. Three key observations were passed as input: the position of the machine agent relative to the environment, the position of the target sphere relative to the environment, and a ray perception sensor on the machine agent that detects whether it is facing a wall, checkpoint, or the target sphere.

Agent's Actions Based on the observations, the machine agent model produced a set of two continuous outputs along the X and Y axes that determined the machine agent's movements.

Agent's Rewards As feedback, the machine agent was rewarded positively and negatively for these specific outcomes. It was assigned a positive reward for reaching the target sphere and for colliding with any of the checkpoints in the environment. We allocated negative points for each time the machine agent collided with any of the walls and each step when the machine agent didn't reach the goal to discourage it from taking too long to reach the goal. In addition to the above extrinsic rewards, Scenario 1 employed an intrinsic reward in the Unity MLAgents package called Curiosity, which rewarded the agent whenever it recorded an observation that was not predicted based on previous observations to promote exploration of the environment (Pathak et al. 2017).

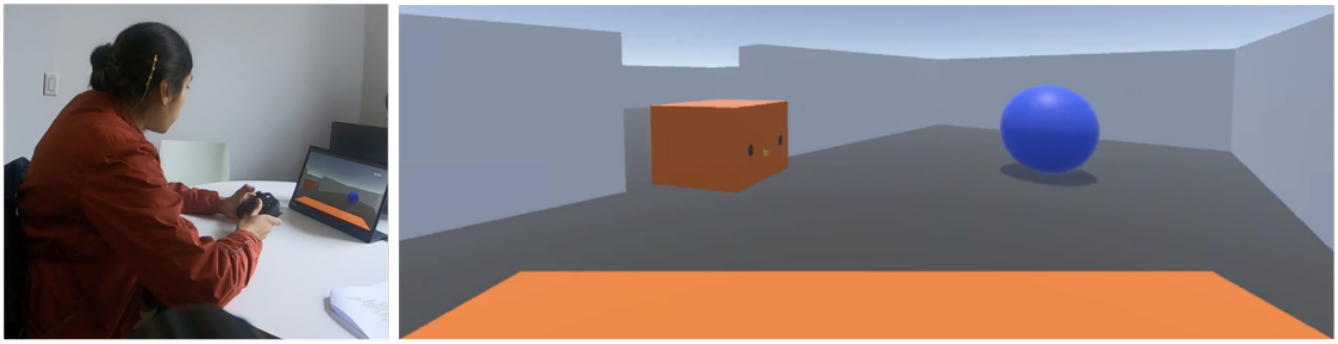

Figure 2: The left image shows how the research participant was situated in the physical experiment room. The right image shows an example of what the research participant saw from a first-person perspective of the virtual environment.

Imitation Learning In addition to reinforcement learning, imitation learning was used in Scenario 1. This strategy of learning from the human agent's demonstration of data was aimed at decreasing training time and simulating a peer-learning experience where the machine agent's training was dependent on the human agent's behavior during the previous round.

Training Walk-through In Scenario 1, the machine agent was trained using reinforcement learning for 2 min to develop a starting model before the experiment. Then, the human and machine played together in game mode, where the participant's movements were recorded into a demonstration file. Then, in the training mode of the next round, this demonstration file was used to train a new policy using imitation learning and reinforcement learning. The learned policy was exported as a new model file for the machine agent in the second round. The process was repeated for subsequent rounds to build on the previous policy. In Scenario 2, we did not use imitation learning, as with the higher difficulty of the scenario, the human agent's demonstrations would derail the agent's training toward reaching the goal.

Background Interviews

After the experiments, we conducted a ten-minute background interview with each participant to record demographic data, educational background, work experience, and familiarity with AI concepts and applications.

Data Analysis

We had a total of 150 rounds of interview transcript video data from real-life and virtual environments (15 participants with ten rounds; roughly 900 minutes of observational data session). Using the constructivist grounded theory approach, we analyzed the session transcript and interview data (Glaser, Strauss, and Strutzel 1968; Charmaz 2014; Bryant and Charmaz 2019). We conducted the initial coding focusing on the participants' different actions and reflections regarding the machine agent and creative problem-solving. We conducted a cluster analysis of those codes to examine emergent themes and developed initial categories of human-AI dynamics and associated actions for co-creative learning.

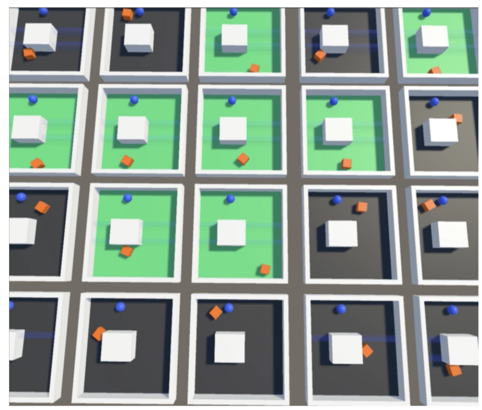

Figure 3: Between the sessions when the human participants were engaged in semi-structured interviews reflecting on the previous round, the machine agent was trained using reinforcement learning techniques and installed with updated policies for the following round.

Using these categories, we conducted a video data analysis of the virtual environment recordings (Nassauer and Legewie 2021; Goldman et al. 2007). The analysis helped to find inconsistencies between the interview transcript and observational video data, refine the categories and associative actions, and develop a cohesive conceptual model.

Results

We identified two major categories of human-AI dynamics in co-creative learning: instrumental and relational.

Instrumental Dynamics

In Instrumental Dynamics, the participants learned new problem-solving strategies using the machine agent as a tool. They often did not recognize its presence in the environment. If they did, they used the machine agent to fulfill their objectives, like pushing it toward the sphere to maximize the points or away from their path to minimize delays. Regarding creative learning actions, the participants actively tested new program-solving strategies using the machine agent. The machine agent was a tool for expanding their conceptual knowledge space about how to solve the problem.

Despite the experiment's mixed-initiative design features, this dynamic was analogous to how a user would have engaged a computer-supported tool. The research participants had the sole initiative in driving the creative process and outcomes. Regardless of the machine agent's generative and learning features, the participants engaged with it with a narrow understanding of its capabilities and efficiently used it to maximize the points.

Relational Dynamics

In Relational Dynamics, the participants learned new problem-solving strategies alongside the machine agent. The relational dynamics were associated with the number of commonalities the participants perceived with the machine agent, like having the same body forms in the virtual space and recognizing the machine agent's ability to learn from their behaviors. One of the defining actions in this dynamic was naming and talking to the agent, as exemplified by the following session transcript from a research participant.

> *Where is Mr. Cube? Hello Cube. Where'd you go? Oh, there, you're you. Spinning cube. Hi. Do you want me to not look at you so you can follow me? Did it fall? Can I just call it a he? I think something about it being a cube makes it seem masculine. Dude, come here.*
> - Participant 3 Scenario 1 Round 2

In addition, the participants approached, engaged, and sought reactions from the machine agent. In this dynamic, the participants are often indifferent toward maximizing the points at the moment. They would spend the entire round testing, observing, and validating their assumptions about the machine's agents' learning abilities.

> *[F]rom my current knowledge and how I interact with Al in my daily life, I use it as a bottler. I expect it to do the things that I ask for. But in here now, I learned throughout this game is that I need to look for it to understand how it moves, what it does, how strategically I need to move. So I felt the Al as a more person kind of type of thing. [...] I never felt this with AI, but now playing it, I was treating it as also like a live thing maybe.*
> - Participant 6 Scenario 1 Round 5

Within relational dynamics, we identified three subcategories: paternalistic, antagonistic, and empathetic.

Paternalistic-relational Dynamics

In Paternalistic-relational Dynamics, the participants acted toward the machine agent like it was their pet, child, or younger sibling. The dynamics emerged when the participants found the scenario not challenging and perceived that the agent was struggling. They expressed joy, pride, and irritation. They felt responsible for the agent's actions and learning progress. They actively taught what they knew and eagerly wanted the agent to follow them.

> *I feel very happy if my training actually works and now we're getting the maximum my point. But that's my goal. I feel like my kid has grown into adults that can go for the ball alone. I don't have to give any training data perhaps. [...] So it was like a baby that didn't know how to do anything, and then I have to demonstrate and then it starts to go. I'm personally doing something to train the data and it's learning from me and I'm teaching the Al something and now it's grown. It's better than before. So it's a toddler now. Maybe it'll be a teenager later.*
> - Participant 10 Scenario 1 Round 4

They could engage in forceful actions like pushing the agent toward the goal, as they would have done in instrumental dynamics. Yet, in these dynamics, they expressed remorse and ambivalence, considering their treatment inhumane despite engaging with the machine agent.

Antagonistic-relational Dynamics

In Antagonistic-relational Dynamics, the participants acted toward the machine agent like rivals. The dynamics occurred when they perceived the machine agent could learn, solve problems, and share the same goal but didn't share the crucial information that could benefit them. They tested the agent to see if they were trying to sabotage their efforts to solve the problem.

> *[I]t felt like [AI] was repulsing me or it's not letting me come near it. No matter how hard I try, it's just, it's getting difficult. It's getting difficult to guide it or control it. It is just pushing me away. Maybe if I try to, it's just this is getting very difficult. It feels like it doesn't want me to tell it what to do, and it's also trying to move away from the goal.*
> - Participant 14 Scenario 1 Round 4

They were actively engaged in new problem-solving strategies but acted adversarially, expressed distrust, and questioned the machine agent's intentions.

Empathetic-relational Dynamics

In Empathetic-relational Dynamics, the participants acted toward the machine agent with comradeship. They perceived that the machine agent was in the same predicament, not knowing the answer to the challenge but sharing the same goal. They expressed empathy and expressed that they were equal in their problem-solving abilities.

> *I think this [Scenario 2] we were both two confused teammates, so I was kind of bonding with it and I kind of understood its feelings, if it has feelings, but I think I was understanding what it was going through. Earlier [in Scenario 1] I was just like, I knew what to do, so it was more like, me waiting for it. This time [Scenario 2] I was like, okay, we'll figure it out together.*
> - Participant 7 Scenario 2 Round 1

They let the agent take the lead in problem-solving while they observe the actions. They were open to the idea that the agent's approach could lead to solutions that benefit them both. While this dynamics seems analogous to how a user would approach computationally creative systems that autonomously solve problems, the passivity of the participants was not constant where they would take the initiative of collaborative problem solving after watching how the machine agent approaches. In addition, the participants were emotionally engaged, often expressing empathetic expressions based on how they perceived what AI would've experienced if it were a human teammate.

> *I was missing the AI. Does it matter? Yeah, because I thought we'll do it together. So yeah, I didn't want to go without it. [...] It was like some people were co-creating away something together, and it felt like I was leaving it behind so it didn't feel nice. But then obviously it wasn't there [in the hidden room], so I had to go and touch the sphere because I was the only one there to finish the route.*
> - Participant 13 Scenario 2 Round 5

Dynamic Fluctuation

We found the dynamics were not constant between and even during the rounds. Two factors may influence the change in the dynamics: the perceived commonalities with the machine agent and the level of challenge of the scenarios. The increased perception of the commonalities could come from recognizing the same design features in their embodied characters in the virtual environment, the machine agent's problem-solving and learning ability, and interactions that reminded them of analogous examples of relations they had with friends, families, colleagues, children, and animals. The perceived challenge was the level of uncertainty the participants perceived in the scenarios. Their relations with the machine agents were affected by their assessment of the problem's difficulty level, the number of unknown factors, and the overall sense of lack of control in the situation.

The actions associated with the two major dynamics shared common characteristics with those related to two types of creative learning. **The actions of instrumental dynamics were consistent with intrapsychological creative learning activity**, where the participants actively used the machine agent to test, combine, explore new strategies, and updated their knowledge about the scenarios. **The actions of relational dynamics were consistent with interpsychological creative learning activity**. The participants constantly verbalized their ideas to the AI, looked for its reaction, and adjusted their beliefs accordingly. It is important to note that the consistency of actions amongst the categories is not conclusive proof that a certain learning has occurred. In future studies, the additional measures can better validate the connections between the dynamics and types of creative learning. In the scope of the current study, however, we note the co-occurrence of the activities is the precondition for creative learning, which is an emergent phenomenon with an activity system.

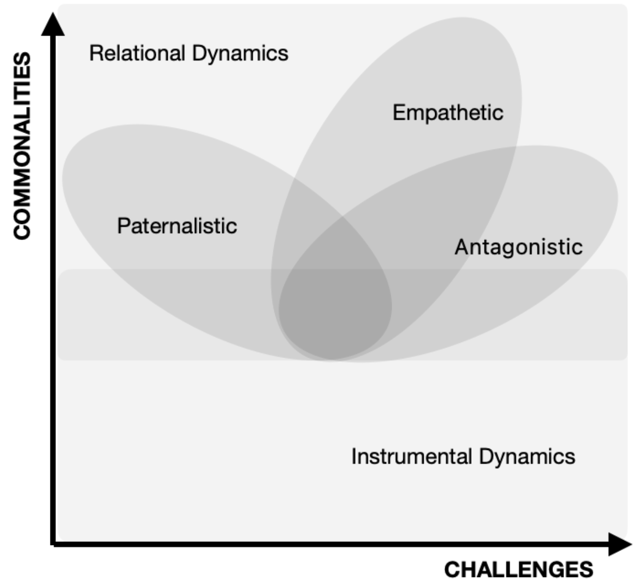

Figure 4: We developed a conceptual model of how the dynamics categories are related based on factors like perceived commonalities and challenges. Throughout the rounds, the human participant's position changes, entering different zones of dynamics.

Discussion

Along with the results, we identified various insights into human-AI dynamics from the study. First, despite the uniformity of the experimental scenarios, each participant had a unique combination of dynamics with the machine agent over time. The initial conditions varied, and participants' perceptions of the agent were affected by their background and preexisting knowledge about AI, training methods like reinforcement learning, and virtual gaming.

Second, the dynamics constantly fluctuated based on the perceived commonalities and challenges. Once the dynamics shifted from instrumental to relational, they tended to stay in the relational dynamics domain. However, the subcategories within the relational dynamics were hard to pinpoint at an exact moment. On an aggregate level, the dynamics categories were identifiable as emergent phenomena when the participant's action was used as a unit of analysis. We need to investigate the additional methodologies to use these categories as a diagnostic classification system.

Third, one dynamic we not better than another in exhibiting creative learning activities. Both instrumental and relational dynamics pushed intrapsychological and interpsychological creative learning activities that could expand the participant's conceptual knowledge. The instrumental dynamics were efficient in testing one's ideas. The relational dynamics, even though they might be paternalistic or antagonistic, drove motivations to engage in different strategies as much as the empathetic dynamics could lead to getting new inspiration from the agent's strategies. The design challenge of future co-creative systems would be how to effectively facilitate various combinations to maximize the expansion of the participants' conceptual knowledge, which all contribute to creative learning.

Lastly, we consistently identified participants' struggles when describing their relations with the machine agent.

They found analogous situations in their prior experience, but they often found discomfort and unease in using those relationships to explain what they were experiencing with the machines. We theorized uncanniness happened when the participants' relations with the machine agent fluctuate between instrumental and relational dynamics.

Conclusion

In this paper, we conducted an exploratory experiment in a virtual environment where the human and machine agents engaged in iterative problem-solving activities using reinforcement learning. We found that the two major human-AI dynamics, instrumental and relational, can be associated with the actions of interpsychological and intrapsychological creative learning. The factors like perceived commonalities and challenges could affect the fluctuation of the dynamics whose initial condition and combination are unique to each participant over time. We found many limitations during the study that can be addressed in future studies. First, the perception of relations is one-directional from the human participant. Besides the actions from the reinforcement learning, the machine agent did not participate in the exchange of ideas as a human peer would have done in an inter-psychological creative learning environment. The interpretation and the initiative of describing the relations were solely on the human agent research participant. Second, the researcher's interpretation of actions was contextual. There were incidents of incongruity between a certain action and the participant's reflection where the researcher had to exercise their interpretation. Third, as the human-AI dynamics were in flux and emergent from the combination of actions, we found the current approach of using action as a unit of analysis was limiting. A different method needs to be used to systematize dynamics concepts for identification and classification. Fourth, there can be a more systematic data collection on the participants' background and creative learning. The current method of self-assessment of technical expertise did not allow for a robust analysis of the factors that might reveal a predisposition to certain dynamics. Future studies can incorporate different learning assessment techniques to better understand creative capacity development along with the current practice of observing the occurrence of creative learning activities. Lastly, the research can expand to examine the relationship between the types of tasks and the current dynamic categories. Comparing open-ended versus execution-focused tasks in a creative process may provide insights into the inclination toward a specific type of dynamics in their co-creative interactions.

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