Think and Play: Designing and Evaluating Human-AI Teaming Dynamics in Gaming Environments

Qiao Zhang, Christopher J. MacLellan
Georgia Institute of Technology
Atlanta, GA 30332 USA
qzhang490@gatech.edu, cmaclell@gatech.edu

Abstract

To investigate Human-Machine Teaming (HMT) dynamics—and how AI capabilities influence team behavior and performance—we propose a series of three studies to explore communication, coordination, and adaptation in HMT paradigms. To support these investigations, we are developing multiple AI agents and using collaborative games as testing environments to evaluate the human-AI team performance. This work contributes to two central topics in HMT research: 1) the bidirectional adjustments that human and AI agents may develop when working as a team and, 2) how different types of AI agents and interventions can impact the teaming efficiency in human-AI teaming.

Introduction

Humans and machines have collaborated for several decades, achieving success across domains such as healthcare, education, military operations and video games (Stowers et al. 2021). Recent advances in artificial intelligence (AI) and machine learning (ML) have resulted in agents capable of outperforming human experts in many tasks, including playing games (Perez-Liebana et al. 2016; Harpstead et al. 2023). However, studies show that AI agents still generally lack the ability to recognize their teammates' knowledge and behaviors, or to respond to novel situations where such awareness is needed (Johnson and Vera 2019). For example, while the OpenAI Five agents(Berner et al. 2019), performed well when playing DOTA2 as an AI team against a human team, the agents struggled to adapt to human players' strategies when cooperating with them.

At a higher level, our work focuses on developing novel, human-guided ML capabilities that enable AI agents to learn from situated interactions with their human teammates during human-AI teaming scenarios. To address the limitations of pre-trained AI agents—particularly their inability to dynamically adjust to human behaviors—and to raise awareness of human-AI teaming research, we propose a series of studies focusing on studying team competencies that are transferrable across contexts (Salas, Reyes, and McDaniel 2018). We will use three games as experimental environments to examine how communication, coordination and adaptation interact with team role assignments and composition (Zhang 2023). Our goal is to better understand the bidirectional adaptations and interactions between humans and their AI teammates, with a focus on trustworthiness and teaming efficiency in human-AI collaboration. Additionally, we aim to explore how different types of AI agent interventions affect team performance, and how knowledge tracing can be applied to improve human learning.

Study Design and Initial Results

Study 1: AI Tutor for a Strategy Game

Several AI systems, such as AlphaGo (Silver et al. 2016), AlphaGo Zero (Silver et al. 2017), and AlphaZero (Silver et al. 2018), have demonstrated their ability to outperform expert human players. However, little research has explored the potential of using deep learning models—which are difficult for humans to understand and relate to—for educational or training purposes. To address this gap, we incorporated principles of intelligent tutoring systems (Nwana 1990), using the game *Gomoku* as a testbed, and developed a strategy tutor for the game from scratch.[1] This Gomoku tutor provides users with either immediate or delayed feedback to support their learning and skill development (Zhang and MacLellan 2022).

We used an open-source implementation of the AlphaZero algorithm designed specifically for *Gomoku*[2] and trained a model on an Nvidia A40 GPU for approximately three weeks. In a pilot study[3] conducted on Amazon Mechanical Turk including more than 300 participants, we observed significant differences in learning outcomes between participants who received feedback during game play and those who did not. These results suggest the potential of using deep learning models to support human learning and strategic decision making.

Study 2: Collaborating with AI Intervention

In addition to AI-assisted reasoning, we aim to understand how different types of agent interventions affect human task performance and contribute to an efficient team. Inspired

[1]https://github.com/qiaozhQZ/Gomoku_flask
[2]https://github.com/junxiaosong/AlphaZero_Gomoku
[3]https://osf.io/5jrq3/

by the strategy simulation game *Mini Metro*,[4]—in which players design subway maps for a growing city and manage passenger transport—we seek to expand the state space by building a 3D/VR game variant. This will let us explore how human and AI agents might collaborate and make decisions as the environment becomes increasingly complex. Using *Space Transit*[5] (Wu et al. 2024), a 3D/VR game developed at the University of California San Diego, we modified the VAL agent (Lawley and Maclellan 2024) to be compatible with this environment by defining six primitive actions that can support the minimal functionality of game play.

The current version of the agent can interpret step-by-step instructions by parsing the prompts from human players, mapping the natural language to the closest game actions, and executing those actions in the game. Pilot study results show that human players achieved better game performance—surviving longer and earning higher scores—when assisted by the agent (Wu et al. 2024). Previous studies have discussed how AI agents can fulfill critical roles and responsibilities within a team (Cooke and Lawless 2021) and have emphasized the importance of human-in-the-loop approaches in human-autonomy teaming (Schaefer et al. 2021). However, limited research has examined the tasks allocation and priority classification in human-AI teaming scenarios. We aim to design a paradigm for multiple types of AI-based intervention to explore 1) the optimal proportion of AI automation in human-AI teaming tasks; 2) the type of AI automation preferred by humans (e.g., ful autopilot, task-based semi-auto pilot, tasks suggestion, etc.); and 3) the combination of intervention type and automation level that yields the greatest throughput for a human-AI team within a fixed amount of time.

Study 3: Coordination in Hybrid Teams

While *Space Transit* provides an environment where humans and AI agents have complete and symmetrical information about the game state, we also aim to study the team dynamics in a collaborative settings where players have asymmetrical information. In the *Dice Adventure*—a turn-based dungeon crawling adventure game developed at Carnegie Mellon University [6] (Harpstead et al. 2023)—three players work together as a team, each controlling a character with unique capabilities to overcome obstacles and achieve individual and team goals. Verbal and textual communications are prohibited, but players can coordinate using a specially designed pinning system. Since there were no predefined meanings of the pins, we use this mechanic to study how team members align and adapt to one another over time.

Using *Dice Adventure* as the environment, we are organizers for a competition[7] at the 2024 and 2025 Conference on Games.[8] Our goal is to replicate the OpenAI Five results (Berner et al. 2019) by developing and training Proximal Policy Optimization (PPO) (Schulman et al. 2017) agents that can perform effectively on an all-agent team and outperform human players. We will also evaluate the performance of PPO agents when placed on human-AI team. We are also developing knowledge-based hierarchical task network agents (HTN) agents using VAL (Lawley and Maclellan 2024) as the infrastructure and insights from gameplay observations from the 2024 competition (Zhang 2024) to inform higher-level behaviors. These agents can learn online, changing their behavior in response to human teammate instruction. We hypothesize that HTN agents will better align with human teammates and adapt to their strategies. Previous work on adaptation has explored its role in human-AI teaming (Zhao, Simmons, and Admoni 2022), the development of adaptive AI teammates (Hauptman et al. 2023), and approaches for evaluating them (Holter and El-Assady 2024). Building on these foundations, we aim to further investigate: 1) how different type of AI agents adapt to align with their human teammates, and 2) how team composition (e.g., number and types of agents on a team) and role allocation affect agent adaptation and, ultimately, the performance of the human-AI team.

[4]https://dinopoloclub.com/games/mini-metro/

[5]https://github.com/xrdesign/Metro

[6]https://github.com/STRONG-TACT/HMT-Game-1

[7]https://strong-tact.github.io/

[8]https://cog2025.inesc-id.pt/

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