A Call for Deeper Collaboration between Robotics and Game Development

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***Abstract*—While robotics and game development have independently achieved significant progress in creating interactive and intelligent systems, a deeper collaboration between these fields could be mutually beneficial. This paper argues for more collaboration, highlighting current limited interactions and proposing directions for future research. We discuss shared foundations such as Artificial Intelligence, Extended Reality, and the increasing use of common tools and standards. We then propose opportunities where game development methodologies can advance robotics (e.g., gamified data collection and richer simulation environments) and where robotics research can contribute to games (e.g., improved NPC autonomy and embodied intelligence). This cross-disciplinary interaction can accelerate innovation and lead to more intelligent and user-centered technologies in both domains.**

***Index Terms*—Robotics, game development, collaboration, artificial intelligence, non-player characters.**

I. Introduction

Robotics and game development are two of the most dynamic fields today, driving significant technological advances in industry and research. Despite their shared fundamental challenges, such as the creation of intelligent agents capable of autonomous behavior in dynamic environments, and the convergence of enabling technologies like Artificial Intelligence (AI) and shared simulation tools, the potential for collaboration remains largely unexplored.

Historically, interactions between these communities have often been opportunistic or project-specific. Examples include adopting game engines for robotics simulation, using game-like interfaces for robot control [1]–[3], or using games as case studies for human-robot interaction research [4]. However, there is potential for moving beyond these ad hoc exchanges toward establishing pathways for knowledge sharing, co-development of tools and methods, and the creation of joint research agendas.

Several factors have hindered more collaboration. A key challenge is that these communities traditionally have different goals and research cultures. For example, game design research typically emphasizes "super-human" performance [5], player engagement [6], narrative immersion [7], game character believability [8], and user experience [9] as target goals, whereas most of the robotics community prioritizes precision of perception, reliability of control systems, or task execution accuracy [10]–[12]. While these differences have driven important innovations in each domain, they can also create obstacles to unified research agendas. Yet, bridging this divide offers compelling advantages: imagine robots that are more intuitive and engaging (inspired by user-centered game design principles [8]), or game environments populated by more intelligent and realistic autonomous Non-Player Characters (NPCs) driven by advances in robot systems.

This position paper argues that fostering a deeper interaction between the game development and robotics research communities, especially given recent advances in AI, is essential to accelerate innovation in both fields. It is important to note that the exploration of synergies between robotics and games is not an entirely novel concept. Other authors have reported the commonalities and exchanges between these two areas. For example, Algfoor et al. [13] reviewed path planning algorithms used in both robotics and video games. The interactive and engaging nature of games has been extensively explored in human-robot interaction research, as reported by Rato and colleagues [4].

This paper is organized as follows: Section II outlines current areas of common interest with existing collaborations between the robotics and game development communities, highlighting shared technologies and tools. Section III discusses underexplored opportunities for mutual advancement, detailing how methodologies and findings from one field can benefit the other. Finally, Section IV concludes the paper with a summary of the potential benefits of deeper collaboration.

II. Common interest areas

While robotics and game development may have different ultimate goals, they have increasingly more shared foundation technologies and methods. This section explores the domains where existing common technologies, tools, or collaborations have been fruitful, but a deeper integration could result in even more advances.

A. Artificial Intelligence (AI)

Robotics and game development share fundamental challenges in creating intelligent agents capable of autonomous behavior in complex, dynamic environments. In both fields, AI has been the most prominent enabling technology driving

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research to address these challenges. Both fields leverage Reinforcement Learning (RL) for optimal behavior learning and Generative AI (like LLMs and VLMs) for natural language interaction, planning, and scene understanding. Furthermore, both fields rely on Human-In-The-Loop (HITL) learning to align AI behaviors with human expectations and increasingly use similar tools and simulation environments.

1) Reinforcement Learning (RL): The principle of RL — an agent learning optimal behaviors through interaction with an environment to maximize cumulative rewards — is applicable whether the agent is a virtual character in a game or a robot in the real world. Therefore, it is no surprise that RL has been a very important technique in both domains. In gaming, RL algorithms have been used to develop artificial players in games like Go, Chess, StarCraft, and Quake III Arena [5], [14]–[16], but also for game testing [17], [18], Procedural Content Generation [19]–[21], or improving the believability of NPCs [8]. In robotics, RL has been extensively used for training robots in tasks such as autonomous navigation [22], path planning [23], object manipulation [24], and bipedal locomotion [25], enabling them to learn from trial and error in simulated or real environments [26]. Both fields struggle with common challenges in RL, such as improving sample efficiency, designing effective reward functions, and ensuring safety and robustness of agent-learned behaviors [26]–[30].

2) Generative AI: Large Language Models (LLMs) and Vision Language Models (VLMs) both work with one of the most natural modes of interaction for humans: natural language. To create a seamless interaction LLMs and VLMs offer an interface that requires no further learning, practice, or specific documentation. It lowers the potential barrier of entry for both games and robotics and is one of the most recent advances that offers great benefits in both fields [31]–[35]. Any improvement in either field can often be transferable between domains: planning [36], and reasoning [37], or automatic generation of narratives [38]. Similarly, the VLMs ability to understand a scene from just raw pixels is something that can have benefits on e.g., a robot's understanding of a scene [39], and in the same way, an NPC can understand its counterpart, but in a game [40]. Understanding the affordances and relationship between objects for grasping or realistic navigation in a social environment is crucial for both robots and game characters.

3) Human-in-the-Loop (HITL) Learning: The challenges behind creating intelligent AI-based agents — whether for developing believable game characters or for robots capable of safe and robust real-world interactions — often stem from the difficulty of pre-scripting all desired behaviors or anticipating all possible scenarios these agents might encounter. Common learning methods for this goal, such as training an RL agent from scratch, or generative AI methods, can be extremely data-intensive and may result in behaviors that are inexplicable, or misaligned with human expectations [41]. Translating qualitative behavior into a mathematical reward function can be a challenging and unnatural process. Human-in-the-Loop learning, for example, in the form of Reinforcement Learning from Human-Feedback (RLHF) [42], offers a possible solution to address these issues.

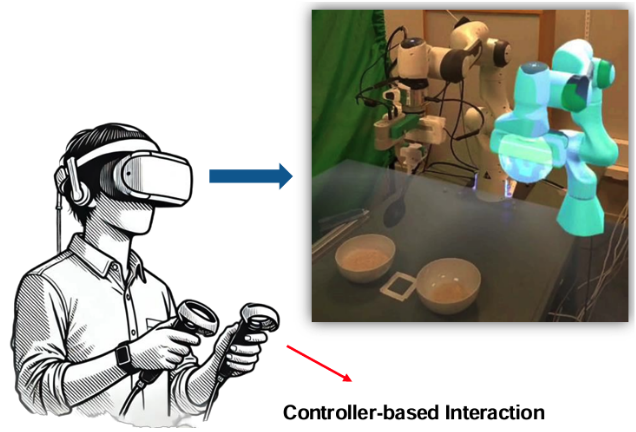

Fig. 1. Example of a controller-based AR robot teleoperation system [3].

Despite the promising results of HITL, most of the examples in games so far focus on either learning a policy to complete a task or reducing sample inefficiency. For example, Zhao et al. [43] used an approach similar to behavioral cloning in which gameplay agents learn behavioral policies from game designers, and Harmer et al. [44] trained agents through a combination of Imitation Learning and RL with multi-action policies for a first-person shooter game. One key component in many video games is the believability of NPCs. Recent research by Milani et al. [45] showed that it is possible to create human-like game agents, but requires extensive reward shaping, which can be difficult to implement without humans in the loop.

In robotics, domain experts or even end-users can more intuitively teach robots new skills, correct mistakes, or collaborate more effectively and safely [46], [47]. The underlying principles of how to effectively elicit, interpret, and integrate human feedback into the learning loop of an AI agent are largely shared, irrespective of whether that agent is a virtual entity within a game or a physical robot interacting with the real world. Consequently, methodological advances in HITL for one domain, such as optimizing human feedback in preference learning for robotics tasks [48], [49], can be adapted to the other.

B. Extended Reality (XR)

Extended Reality (XR) — including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) — although not initially developed for gaming nor robotics, has led to extremely successful games such as *Pokémon GO*[1]. XR applications are typically developed using tools that are also used for the development of games and robotics technologies. For example, game engines like Unity [50] are frequently used for creating XR experiences, which in turn are increasingly

[1] https://pokemongo.com/

used for Human-Robot Interaction (HRI), robot control, and teleoperation [2], [51]–[53] (see Figure 1). These technologies allow users to visualize robot states, plan tasks in a virtual overlay of the real world, or even remotely operate robots with intuitive, game-like interfaces. While less explored for these purposes, XR applications can also facilitate novel forms of remote human-robot collaboration, or create new types of interactive entertainment where physical robots are extensions of virtual experiences.

C. Standards and Open-Source Tools

The development of shared standards and open-source tools is crucial for reducing friction and accelerating interdisciplinary collaboration between different communities.

Among shared tools of these two communities, Unity [50] is one of the most prominent. This widely popular game development engine is increasingly adopted in robotics, especially for simulation and testing AI-based algorithms, due to its powerful 3D rendering and physics capabilities (see Figure 2). Unity already offers several integrations with ROS[2], one of the most common standards in robotics. Furthermore, widely adopted open-source AI libraries such as TensorFlow[3] and PyTorch[4], as well as physics engines like Rapier[5], also serve as a common ground for many researchers in both fields.

Another example is the Universal Scene Description (OpenUSD), initially developed by Pixar, which is emerging as a standard for describing, composing, and interchanging 3D scenes and assets. Its adoption is gaining some traction in both robotics [54] and game development, as evidenced by its native integration into game engines such as Unreal Engine. More recently, a collaborative effort involving NVIDIA, Google DeepMind, Disney Research, and Intrinsic to define specific OpenUSD asset structures tailored for robotics applications was announced[6], which can streamline the process of creating and sharing robot models and simulation environments.

The adoption of open standards like OpenUSD, together with the use of shared open-source simulation software and AI toolkits, is therefore critical for creating shared approaches, methodologies, and benchmarks, benefiting both fields.

III. Opportunities that could be further explored

We argue that a deeper exchange between the game development and robotics communities can be mutually beneficial. In this section, we discuss possible ways that we consider less explored so far, in which results from one of the fields can benefit the other. For example, game development methodologies can benefit robotics, for instance, through gamified data collection to efficiently train large AI models, and by providing richer simulation environments for training and testing robotic algorithms in a wider range of scenarios. On the other hand, recent developments in robotics research can offer solutions to automate complex game development tasks such as improving NPC autonomy and (embodied) intelligence, and in developing more realistic game environments. A summary of these opportunities is listed in Table I.

[2]https://www.ros.org/

[3]https://www.tensorflow.org/

[4]https://pytorch.org/

[5]https://rapier.rs/

[6]https://developer.nvidia.com/blog/announcing-newton-an-open-source-physics-engine-for-robotics-simulation/

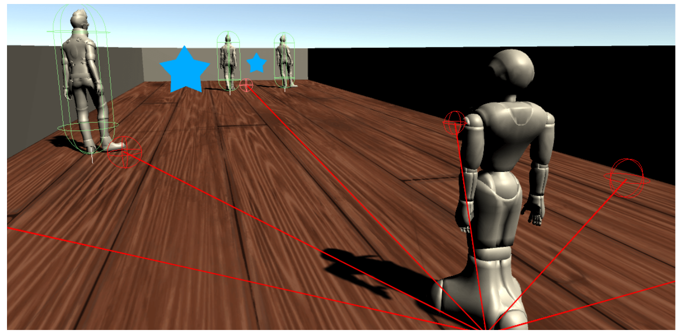

Fig. 2. Example of a robot social navigation environment built in Unity [55] for eliciting human preferences of robot trajectories. The robot has to navigate to the end goal while avoiding humans walking in the environment.

A. From Games to Robotics

1) Gamifying Robotics: Despite some existing work on applying game design and development principles in the context of robotics, we see this as a mostly unexplored opportunity in many subareas, such as the ones we discuss below.

Data Collection. Modern AI models, such as Vision-Language Models (VLMs), which are becoming quite popular in robotics, as well as learning paradigms such as imitation learning and RL, need large amounts of data [30]. In robotics, the data for training these models often consist of human demonstrations either teleoperating a robot or interacting directly with the environment, which is very expensive to collect and quite tedious for the human "demonstrators". Therefore, data acquisition has been a critical bottleneck for creating robust models for real robotic applications [32]. This is where gamified data collection could emerge as a promising application. For example, games built for data collection purposes could be engaging and scalable platforms for acquiring data far more effectively than many traditional methods (usually paying crowd workers). There are already a few works along these lines. For example, The RoboCrowd project [56] uses crowdsourcing principles combined with gamification elements – such as leaderboards and engaging manipulation tasks – to facilitate the in-person collection of bimanual robot demonstrations within a public university café setting. One of the first efforts in this direction was The Restaurant Game [57], a crowdsourced corpus collected from people playing an online multiplayer role-playing game and used to statistically model context-sensitive patterns of behavior and language, with dependencies on social roles and object affordances. As our dependency on large data-driven AI models continues to grow, gamified data collection methods will become increasingly more relevant for advancing robotics research and applications.

TABLE I

SUMMARY OF OPPORTUNITIES FOR MUTUAL ADVANCEMENT BETWEEN ROBOTICS AND GAME DEVELOPMENT

Source field	Opportunity area	Contribution from source field	Potential impact on target field
Games	Gamifying Robotics	Games to scale data collection, robotics competitions and improve assistive robot scenarios.	Enables lower-cost, engaging data collection, and improves HRI.
	Rich Simulation Environments	Realistic video games as digital sandboxes for robotics research.	Valuable testbeds for complex algorithms and safe simulation of hard-to-replicate scenarios.
	Educational Platforms	Educational robots with game-like challenges to teach robotics and general STEM skills.	Engaging tools for learning basic robotics and advanced skills like drone or flight simulation.
Robotics	NPC Autonomy	Robotics perception and decision-making algorithms to create autonomous NPCs.	More believable, dynamic, and intelligent NPCs.
	Embodied Intelligence	Transfer robotics' spatial intelligence and situated interaction capabilities to game characters.	NPCs that meaningfully engage with virtual worlds, their bodies, and surroundings.
	Digital Twins for Game World Creation	High-fidelity, data-driven digital twins of real-world locations and robotics physics simulators.	Access to realistic, pre-made environments, lowering asset creation costs and improving fidelity.

Robotics Competitions. In addition to robots developed for sports, like table tennis [58] or soccer[7], robot competitions are significant drivers of academic research. Major robotics conferences such as ICRA (International Conference on Robotics and Automation) and IROS (International Conference on Intelligent Robots and Systems) regularly include several competitions, many of which are structured around game-like scenarios where robots interact with physical objects and dynamic environments. Examples include autonomous navigation through obstacle courses (e.g., The BARN Challenge[8]), complex manipulation tasks (e.g., the Robotic Grasping and Manipulation Competition[9]), and even robot sports like RoboCup. These competitions not only provide common benchmarks for comparing different approaches but also foster a collaboration. Moreover, they often showcase a bidirectional influence: game design principles inspire engaging and complex robotics challenges, while advancements in physical robot interaction can, in turn, spark new ideas for interactive entertainment and real-world applications. Integrating game-design principles holds potential to further improve the design, engagement and impact of robotics competitions.

Human-Robot Interaction. Gamifying elements can be used to improve user engagement and motivation while interacting with robots. Here, we focus mainly on leveraging game mechanics to improve the interaction process, rather than using games as a context for human-robot interaction, which has been fairly explored already [4]. In socially assistive robots [59], a popular tool for helping people in education or healthcare applications, gamification could hold promise. While some socially assistive robots used in stroke rehabilitation, for example, already include gamified elements in exercises [60], the main purpose of this research was to investigate the presence of the robot instead of the game elements. We see further opportunities not only in therapy and motor rehabilitation but also in other applications like education or social skills training, where repetition is crucial. Game mechanics such as points, levels, rewards, and immediate feedback can make these scenarios more enjoyable and encourage users to keep interacting with the robot.

Gamified elements can create highly engaging, but also sometimes even addictive experiences (as observed in certain social media platforms and immersive games) [61], which bring ethical considerations to these approaches. Designing systems that are highly captivating to encourage large data contribution needs careful considerations regarding user autonomy, data privacy, the potential for unintended user exploitation, and the societal impact of employing such engaging experiences for data collection purposes.

2) Richer Simulation Environments: Modern video games (like AAA titles and car simulators) can offer a valuable resource for robotics research, helping to create complex "digital sandboxes" that could be used for training and testing perception and decision-making algorithms [62]–[65]. Virtual simulations are invaluable for scenarios that are costly, dangerous (like road traffic accidents or training robot-assisted surgery [66]), difficult to replicate physically (such as deep-sea, space environments), or require exposing robots to a wide range of situations to improve their robustness. These environments could also be populated with NPCs, allowing researchers to conduct interaction experiments (i.e., experiments one might not want to do with real humans) that would be unsafe or unethical to perform otherwise. Techniques like automatic Procedural Content Generation (PCG) [19]–[21], quite popular in game development research, can be relevant here to automatically create diverse novel scenarios for comprehensive testing of how robots interact with their surroundings.

Furthermore, the real-time performance capabilities inherent in game engines is crucial for many robotics applications, although this often involves trade-offs between speed and simulation fidelity.

3) Educational Robotics: Educational robots with game-like features are very helpful tools for students to learn new skills. For example, programs like the FIRST LEGO League[10] use fun, mission-based challenges to help children learn robot programming. These tools could help not only

[7]https://robocup.org/

[8]https://2025.ieee-icra.org/event/the-barn-challenge-2025/

[9]https://sites.google.com/view/rgmc2025

[10]https://www.firstlegoleague.org/

students learning basic robotics but could also be used more to train complex skills, like how to fly drones or airplanes in complex simulation environments.

B. From Robotics to Games

Advances in robotics research have the potential to automate certain aspects of game development. Traditionally, efforts in game research have focused on areas like gameplay testing and validation, level design, and Non-Player Character (NPC) autonomy. By leveraging AI developments from the robotics community to automate some of these aspects, game designers can allocate more time and resources towards the creative and high-level aspects of games.

1) NPC Autonomy: A key area that could benefit from such integration is the intelligent autonomous behavior of NPCs. Current game AI often relies on predefined scripts or relatively simple decision-tree logic, which can lead to predictable and sometimes unrealistic NPC actions [67]. Principles and techniques from robotics research, particularly from human-robot interaction, could be used to improve NPCs, making them more believable and dynamic. For example, techniques for human intent prediction [68], eye-gaze detection and generation [69], automatically generating expressive behavior [70]–[72], or research in multiparty HRI for detecting conversational groups [73] and interact socially with groups of different sizes [74]. Furthermore, algorithms developed for robot navigation [75] have a strong potential to improve pathfinding of NPC behaviors, and social navigation benchmarks such as SEAN [76] could be beneficial in gameplay testing or novel level design.

2) Embodied Intelligence: Virtual game-like environments offer a dual benefit: they serve as powerful testbeds for embodied AI research — with platforms like Habitat [77] or games such as Minecraft [78] often used to train embodied agents in tasks like navigation, instruction following, and tool use, which are relevant for both robots and games. In games, a strong application for these environments is improving how NPCs understand and interact meaningfully within these virtual worlds.

A significant contribution from robotics to game development lies in grounding NPC interactions with their environment. This is a feature still rather underdeveloped in current game AI but central to robotics applications [32]. The ability of an agent to perceive, reason about, and physically interact with its three-dimensional surroundings is an essential research topic in robotics and computer vision, which has been advancing drastically due to LLM research [79]. Robots must understand spatial relationships, object properties, and the physics of interaction to operate effectively in the real world. Transferring this level of spatial intelligence to NPCs could lead them to be perceived as more believable and intelligent. Recent research, such as Google's Gemini Robotics-ER [80], which focuses on enhancing spatial and temporal understanding for tasks like object detection, trajectory and grasp prediction, and 3D scene comprehension from multi-view inputs, is directly applicable to creating such interactive and spatially aware game agents.

Furthermore, the emphasis in robotics on situated interactions [81], where an agent's behavior is dynamically coupled with its current context, is highly relevant for advancing both the robotics and gaming communities and can greatly improve NPC realism. This realism extends beyond task-based interactions to encompass believability in how NPCs present themselves and engage with players or other entities. Humans often perceive intelligence and intent through body language and other non-verbal cues; similarly, creating robots and NPCs that exhibit believable behaviors through such subtle interactions is a shared challenge [8]. This aspect is a common focus for researchers in social robotics and Human-Robot Interaction [70], [82], [83]. Their findings could be further explored in the believability of game characters.

3) Digital Twins for Game World Creation: The creation of highly realistic game worlds, such as full cities, is a major content creation bottleneck and cost driver in game development (e.g., the significant investment in creating realistic environments for games like Grand Theft Auto[11]). The robotics community is already heavily invested in mapping and developing high-fidelity, data-driven simulation environments [84], [85]. These digital twins, built for robot training and testing, are often detailed and physically accurate replicas of real-world locations [86], [87]. This ongoing work in robotics could provide game developers with a source of pre-made, highly realistic environments, reducing the initial burden and cost of asset creation for true-to-life games. Other efforts, such as NVIDIA's Omniverse[12], that used OpenUSD as a standard, could further streamline the creation of realistic gaming experiences.

The availability of open-source physics engines, originally developed for robotics, could also play a key role in creating these digital twins. Platforms like PyBullet[13] or, more recently, Newton[14], provide researchers and developers with access to advanced physics simulation capabilities.

IV. Conclusion

This paper argues for the largely unexplored potential of deeper collaboration between the robotics and game development communities. Shared interests in AI (such as RL and generative models) and common tools are becoming more common, but more could be done. The long-standing focus on autonomy within robotics, for example, can advance game AI and development; in return, games offer robust platforms and methods for robot simulation, data acquisition, and training. While we acknowledge the challenges of these efforts, such as the need for domain-specific tuning and hardware-software

[11] https://www.cnet.com/tech/gaming/will-gta-6-be-the-first-100-game-we-do-the-math/

[12] https://www.nvidia.com/en-us/omniverse/

[13] https://pybullet.org/wordpress/

[14] https://developer.nvidia.com/blog/announcing-newton-an-open-source-physics-engine-for-robotics-simulation/

co-design, this collaboration can provide unique opportunities for innovation in both communities.

There are certain ethical considerations and challenges that may arise from these synergies, for example, when leveraging game design principles for data collection in robotics. Similarly, the application of AI advances from robotics to games should take into account the impact on gameplay and user experience, avoiding the creation of extremely complex or unpredictable game characters.

Despite the differences in research goals and publication cultures, the convergence of enabling technologies and shared tools offers a strong foundation for this effort. Promoting interdisciplinary workshops, joint research projects and establishing common benchmarks and frameworks (using the already common tools and the research challenges discussed in this paper) could build a common ground for collaboration. Ultimately, overcoming the historical separation of these communities to actively foster joint research could be extremely beneficial for both, as it can accelerate innovation, resulting in more intelligent agents (virtual or robotic) and better games.

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