Playground+: an AI-MR System for Adaptable Open-Ended Family Physical Activity Play

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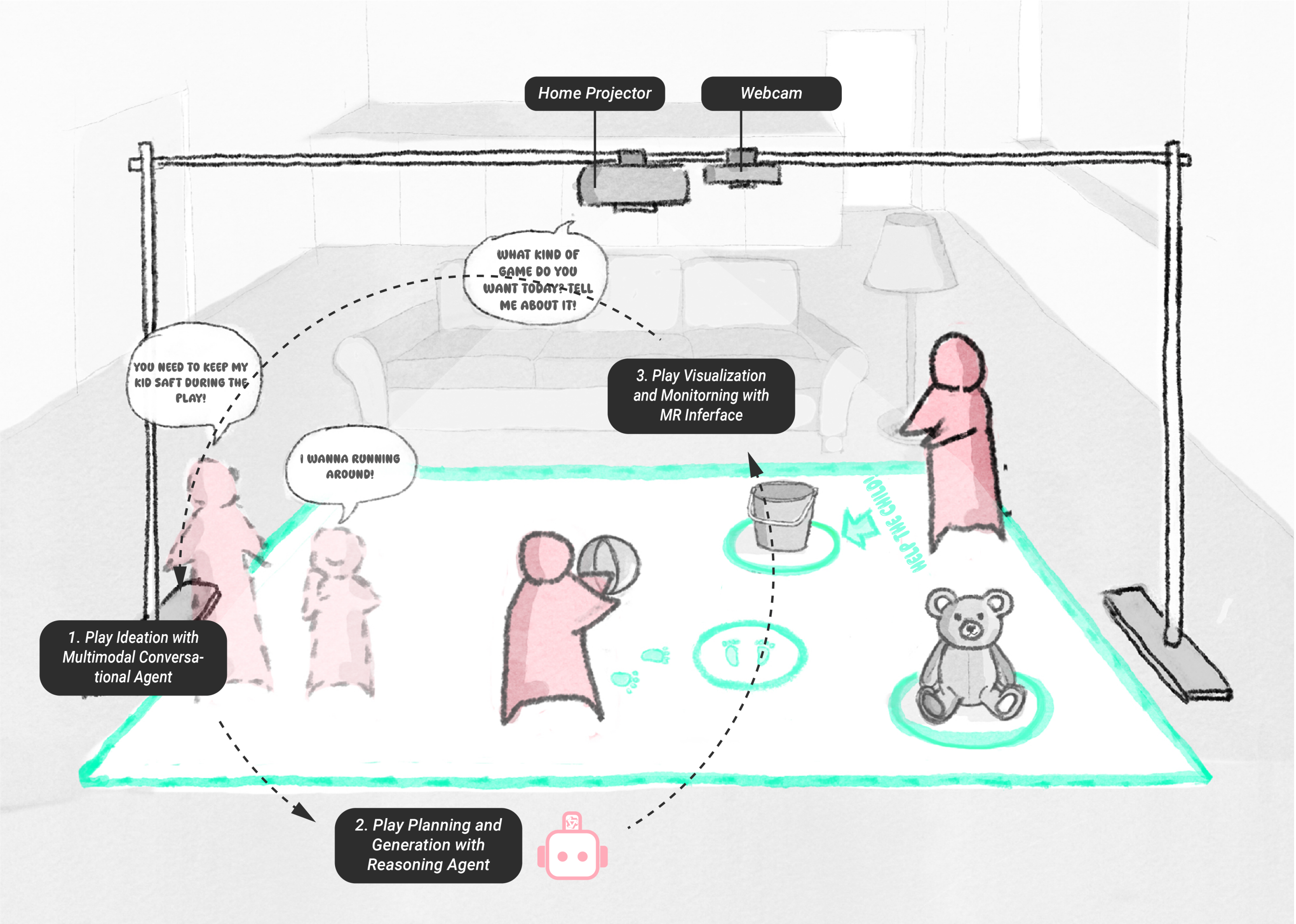

Figure 1: *Playground+* is a projection-based AI–MR system designed to support family physical activity play (PAP). Using a webcam and a home projector, the system supports the ideation, generation, and guidance of diverse PAP activities.

Abstract

Physical activity play (PAP) is vital for children's physical, cognitive, and social development, and previous systems and research have explored how various technologies can support it. However, existing approaches often offer limited game choices, rely heavily on family initiative for ideation, and do not align well with everyday, open-ended play practices. AI-augmented mixed reality (AI-MR) systems offer new opportunities through improved contextual awareness, support for play ideation that lowers barriers for families, and wearable-free visual guidance. We present *Playground+*, a projection-based AI–MR system that combines computer vision and large language models to ideate, generate, and guide PAP. Using a ceiling-mounted projector and webcam, the

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system delivers multimodal guidance that accommodates different parental roles and children's developmental levels. Future work will focus on designing temporal and social support, exploring different possibilities of open-ended play, comparing with spatially flexible solutions through user studies, and addressing technical and deployment challenges.

CCS Concepts

• **Human-centered computing → Interactive systems and tools**; *Collaborative and social computing systems and tools.*

Keywords

Children, Physical Activity Play, Artificial Intelligence, Parent–Child Interaction, Home Environment, Embodied Interaction

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1 Introduction

Physical activity play (PAP) is a term primarily used in research on children's play, referring to moderate-to-vigorous bodily play that involves dynamic engagement, physical coordination, and spatial interaction [22, 26]. PAP plays a critical role in children's physical [2, 3, 26, 31], cognitive [27, 28] and social development [1]. Commercial products and systems have long supported family PAP, including home exercise applications such as Tinatiantiaosheng [1] and interactive systems and devices such as Nintendo Ring Fit Adventure [2]. In everyday settings, PAP often takes the form of open-ended play. Open-ended play lies between structured games and free play, and often shifts between the two within a single session. It combines the benefits of skill development with creative expression by giving children autonomy to guide the direction of the activity [5]. Prior research suggests that this form of play reflects children's natural play patterns and often involves bodily movement [1, 26]. Therefore, supporting open-ended play provides a promising direction for designing for PAP.

While HCI research has explored a wide range of technologies to support PAP, from simple GUI-based applications [19], to interactive environments enhanced through tangible or ambient interaction [12, 30] or Mixed Reality (MR) [10–12, 16, 18, 20], their application in family contexts remains limited [21, 23]. As a result, although these systems demonstrate the potential to provide instruction and utilize the physical environment, they have seen limited adoption to support open-ended play in everyday, long-term family settings. This limitation is often reflected in fixed game formats and restricted variation. Moreover, they introduce novel forms of play that do not align with everyday PAP practices. Recent work [15] suggests that generative AI may offer a potential way to address these limitations.

Generative AI has been widely used in different stages of game design [9, 29] and player assistance [17]. Recently, large language models (LLMs) have been used for tasks such as content generation [6, 8, 9] and game mechanism design [29]. Although most work focuses on supporting professional designers, it could also lower the barrier for lay users to create games [29]. For instance, recent research has used generative systems to automatically create environments and reward mechanisms for agent learning [7]. While not situated in a playful context, the generated challenges can be interpreted as physical play, suggesting the potential of using generative AI to create PAP experiences.

Supporting family PAP further requires an "interactive playground", which is defined as "an assembly of allocated resources (household items, times, spaces) that alone or together, encourage and foster either game or play spaces, or both" in previous family-related work [23]. While it emphasized actively improvising play with available household resources, such improvisation can be enhanced by systems that coordinate and repurpose these resources collaboratively. Recent AI–MR approaches demonstrate better contextual awareness of the physical environment [4], suggesting their potential in facilitating play ideation in domestic settings. Among existing approaches, projection-based systems are frequently adopted as the MR strategy for physical play [10, 11, 16, 20], as the high physical demands of PAP make most wearable devices impractical, while collaborative play benefits from a synchronized view of the play space [10, 11, 16, 20].

With their ability to perceive physical and social context, lower barriers to create developmentally beneficial play for families with limited game design experience, and provide wearable-free visual support, projection-based AI-MR systems represent a promising direction for family PAP. Building on previous empirical work on domestic PAP [15, 23], we introduce *Playground+* as an initial exploration of how to design adaptable and context-sensitive AI-MR systems for family PAP that address these challenges.

2 Playground+

Playground+ is a projection-based AI–MR system designed to support PAP for families with children aged 6 to 10, corresponding to early-to-middle childhood, a stage characterized by frequent locomotor and socially coordinated physical play before the shift toward more structured activities [26]. The system uses computer vision to capture environmental context and state, and LLMs to help ideate and plan PAP activities and generate multimodal instructions including audio and visual outputs from simple geometric cues to text and image content. The projection-based MR renders instructions to guide families during play.

2.1 Design Goals

Based on the gaps identified in previous work [15, 23], including the lack of flexible and diverse support for everyday PAP activities, maintaining temporal and spatial coherence during play, addressing imbalances in cognitive abilities between children and parents, and providing physically embodied guidance beyond verbal instruction, our goal is to create a system that: (1) provides stable spatial planning and instruction; (2) supports the ideation and adaptation of

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[1] TianTianTiaoSheng is a Chinese mobile application that facilitates jump rope activities. https://www.tiantiantiaosheng.com/

[2] Ring Fit Adventure is a Nintendo Switch exergame that turns full-body physical exercises into a role-playing adventure using motion-sensing accessories. https://www.nintendo.com/us/store/products/ring-fit-adventure-switch/

diverse PAP activities; and (3) facilitates family co-play by accommodating different participation patterns and levels of cognitive development among children and parents.

2.2 System Design and Implementation

Playground+ is designed to be easily deployable at home using a ceiling-mounted home projector (JMGO P5X) [3] and a webcam (UGREEN CM827). We used an adjustable photography stand sized to the room and temporarily mounted both devices on the stand for testing. The devices were powered and connected via cables routed along the walls and stand, and connected to a personal laptop that runs the system (see Figure 1).

To address design goals, the system consists of three components: (1) a multimodal conversational agent that perceives spatial states and interprets family preferences; (2) a reasoning agent that uses a back-end AI model to produce diverse, detailed, and executable play plans per request; and (3) a runtime engine that renders visual cues in-situ for family players and supports monitoring of safety, physical states, and play intentions.

2.2.1 Multimodal Conversational Agent for Perception and Context Interpretation. This component manages how the system perceives the environment and provides up-to-date contextual information. To meet privacy requirements for in-home deployment, data collection is limited to real-time processing. No video is recorded. Audio is temporarily transcribed for LLM processing. Only structured scene metadata is stored locally during runtime and deleted after each session. No facial recognition is used, and any personal information is optional and limited to the current session. Given the diversity of household items, we use the YOLOE model [4] to support open-vocabulary object detection. Detected entities' labels and bounding boxes are written into a state JSON file. Since it is inconvenient to let families use tangible input devices during PAP, we choose the conversational user interface (CUI) to capture participants' intention and interpret it with LLM. Both scene state and context are provided to the reasoning agent and runtime engine.

2.2.2 Reasoning Agent for Spatial Planning. To support flexible ideation and the creation of everyday PAP among children, we adopt a hybrid approach in which LLM reasoning [5] supports the ideation of play forms and rules, while primitives convert these ideas into executable representations. In our prototype, end-to-end game generation, from finalized user input to executable visual cues, takes approximately 1-2 minutes, including retries and backtracking when validation fails.

The primitives include condition checks, geometry rules, and spatial cue types to ensure that the generated content is controllable, safe, and aligned with the play intention. We collect them from taxonomies in the literature [14] and use LLM to brainstorm a wide range of common PAP activities, a method widely used in LLM-related research [13]. Then, we analyze the spatial relationships of the game elements according to the rules of each play. Figure 2 illustrates the spatial instruction primitive as an example.

LLM reasoning translates context and scene state into a structured play specification and effects through three stages. *Game reasoning* defines the semantic details of a PAP. These include the phases of play with entry and exit conditions and required instructions; spatial components including both existing entities in the environment and additional visual overlays to be generated for the play; and their spatial relationship. *Specification reasoning* converts the generated game content into an executable specification through logical restructuring. Each phase comprises three stages: *enter*, *during*, and *exit*. It then validates the result against the defined primitives. *Effect reasoning* determines the visualization. While this stage is largely deterministic and driven by geometric primitives, LLM is used to adjust unreasonable parameter values and repair cases not covered by those primitives based on the context. All spatial elements are derived from and constrained by detected scene entities and global boundaries, ensuring that all instructions are desired and do not extend beyond the defined playable area.

2.2.3 Runtime Engine for Visualization and Monitoring. This component renders spatial instructions produced by the reasoning component using Tkinter in Python. All visual elements are positioned and drawn on a black background, ensuring that only instructions are projected onto the floor. Meanwhile, a global update module monitors runtime conditions, such as early exits, unexpected or potentially unsafe objects. During play, the runtime decision loop evaluates and monitors phase conditions at 0.2-second intervals, and visual cue rendering refreshes at 50 milliseconds, enabling responsive embodied feedback during movement. Visualization is designed to accommodate different patterns of parental participation and differences in cognitive abilities between parents and children. When parents act as bystanders, the system provides monitoring by detecting unexpected objects, obstacles, or unsafe conditions, highlighting them visually, and providing audio alerts to prompt parental intervention. When parents participate as co-players, the system presents differentiated instructions: children receive audio guidance and animated cues, such as footprints, to indicate actions and movement paths, while parents are provided with more formal instructions using arrows and text. To accommodate the developing physical abilities and intentions of children, the system also includes exit mechanisms that are activated when players leave the play area or explicitly indicate that they wish to stop, for example due to fatigue.

2.3 Play Flow

To use the system, families install the devices above a designated play zone (e.g., a cleared area in the living room or a children's play mat) and bring selected household objects or toys to this space. Once a participant enters the space, the play session begins. The system first asks family members to communicate their needs by answering four predefined questions about personal information (name and age), play duration, play preferences, and desired constraints. It may request additional details until sufficient context is collected to design a PAP session. Then, the system generates the play activity and prompts the family to prepare or take a short break while processing. When the instructions are ready, family members follow the projected guidance on the floor to complete the round. After each round, families can replay the same activity without changes,

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[3] In a room with a ceiling height of 2.7 m, the calibrated projection area on the floor is approximately 2.7 m (length) × 1.8 m (width); a higher ceiling increases the projection area proportionally, depending on the projector's throw ratio.

[4] https://docs.ultralytics.com/models/yoloe/

[5] We use the qwen-plus model provided by Alibaba Cloud. https://qwen.ai/apiplatform

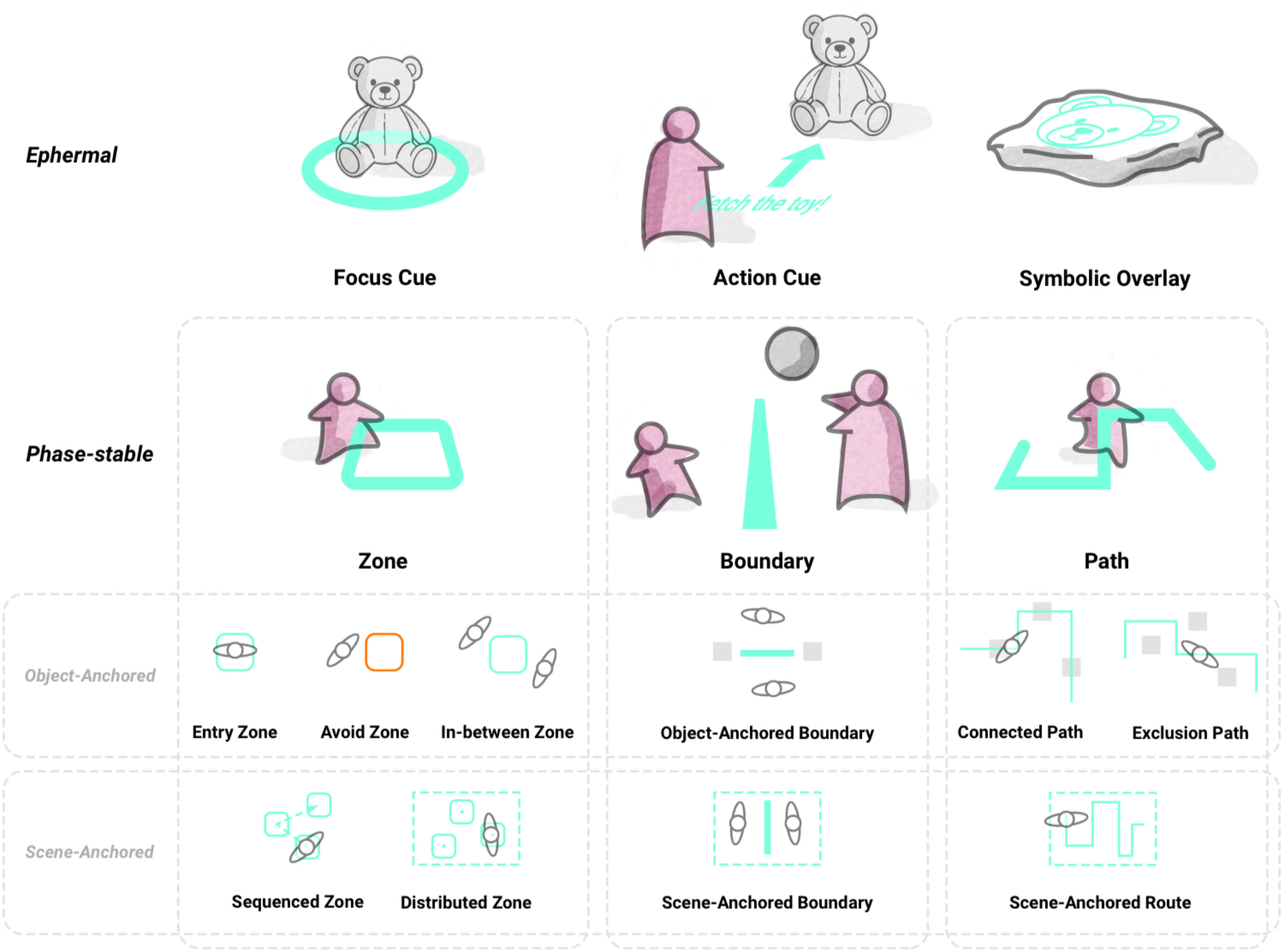

Figure 2: The design of spatial cue primitives. *Ephemeral* cues move with their associated entities and are used to indicate anticipated actions, targets, and directions of movement. *Phase-stable* cues persist throughout a phase and remain at fixed positions, functioning as game elements.

regenerate the activity with modified rules or preferences, start a new session from scratch, or stop and exit. To illustrate the diverse play forms the system supports, we present example outputs in Figure 3.

3 Discussion and Future Work

In this system prototype, we focus on designing spatial reasoning, planning, and visualization for family PAP support to address the limited physical embodiment of current multimodal generative AI systems, such as AI chatbots. Our next step is to conduct a pilot study to assess the feasibility and refine the current design regarding spatial support. However, through system design and self-testing, we also identified several open questions that motivate future work.

First, while our current design prioritizes spatial guidance as a core challenge for family PAP, existing theory and literature suggest a broader design space. Montola et al. [24] propose that pervasive games can be expanded along spatial, temporal, and social dimensions, a framework that has been applied to family PAP in previous work [23]. As noted by Hughes [14], PAP has different categories. However, not all of them require spatial guidance. For example, activities such as jump rope may only require temporal or social support, such as counting and encouraging, rather than spatial instruction. As a next step, we plan to extend the system with temporal and social support modules, including mechanisms to assess and balance family members' engagement, a memory module to enable long-term personalization for in-situ deployment, and enhanced context awareness through monitoring participants' state over time (e.g., fatigue or loss of focus).

Second, our system opens opportunities to examine how different design strategies related to form and space for AI-supported PAP shape development goals in family settings. In terms of forms, Matjeka et al. distinguish between “game” and “play" according to

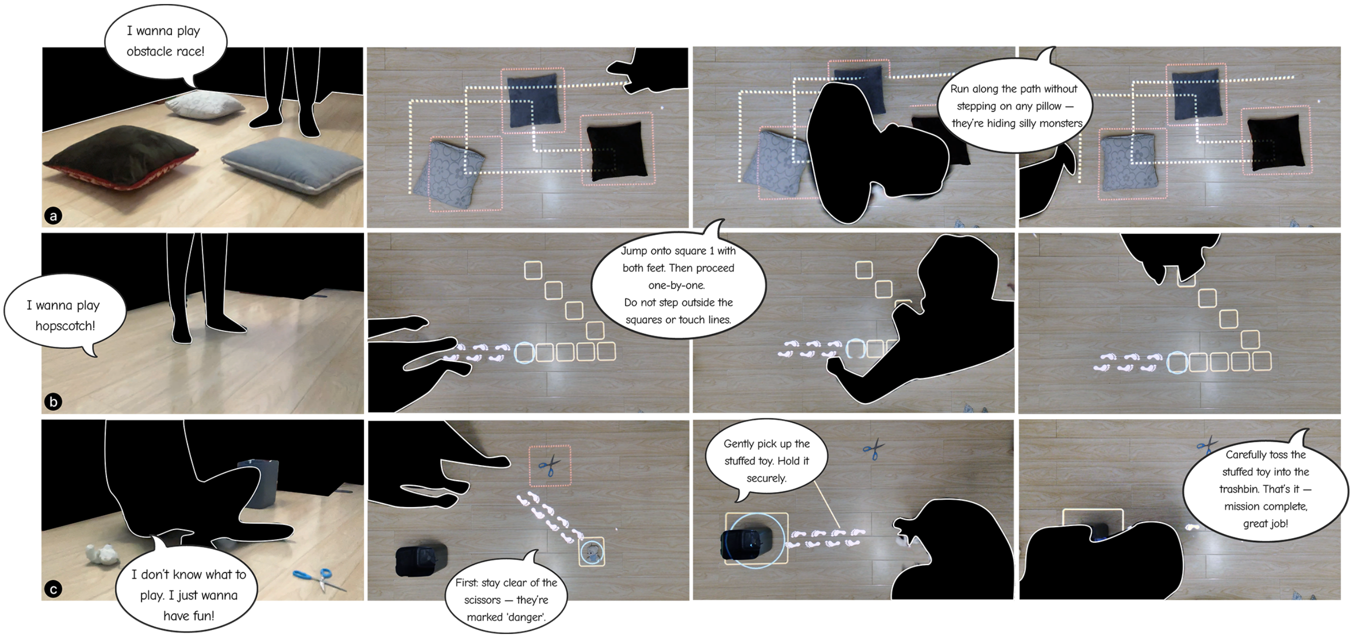

Figure 3: Example outputs of *Playground+*: (a) Obstacle Race, where household objects are used as obstacles; (b) Hopscotch, generated as request when no objects are present in the scene; (c) Toy Toss, ideated and generated by the system when the user shows no preference.

whether the structure is predefined, while Segura et al. highlight technology choice as a central design challenge to support these different PAP experiences [22, 25]. Previous work documents frequent moments of improvisation during PAP despite preset rules [23]. In Playground+, open-endedness is mainly at the level of session configuration: families decide which objects to use, what type of play to engage in, and which rules to follow. The LLM then generates diverse scenarios based on these inputs. Bekker et al. discuss the need to balance abstract play ideas with concrete interaction in open-ended play [1]. Our prototype reveals a similar boundary. Although generative AI expands the range of possible play scenarios, physical play still requires a certain level of procedural structure to maintain temporal coherence. How this boundary affects the format of open-ended play and mediates between goals such as creativity and self-expression and functional outcomes such as physical and social development remains an important direction for future research. From a spatial perspective, our system operates within a designated PAP area. In contrast, previous work on pervasive games explores the full-room and cross-room deployment of artifacts, effectively turning the entire home into a playground [16, 23, 24]. Recent studies also show that families already use AI chatbots with multimodal capabilities on their phone or home robot to conduct PAP at home, which is more flexible in terms of space [15]. Comparative user studies across these approaches could help clarify the trade-offs between spatial arrangement and flexibility, as well as their implications for risks and benefits regarding development goals.

Lastly, future work also involves addressing several technical considerations to support robust in-home deployment. Occlusion from players' shadows may introduce safety and usability concerns. To mitigate this, we reduce instructions to simple geometric shapes, making brief occlusions less disruptive. Future work could further address this limitation through solutions such as multi-projector setups [10]. While YOLOE enables the detection of many common household items, switching to models specifically trained on household objects would enhance the reliability of geometry generation and condition evaluation during play by improving detection accuracy and temporal stability. Similarly, incorporating multi-camera tracking or depth sensing could mitigate limitations related to perspective distortion and occlusion. Beyond sensing, simplifying device setup and installation is critical for everyday family use. Exploring more integrated hardware configurations, such as replacing the laptop with a customized microcontroller and developing portable projector–camera assemblies, could substantially lower barriers to adoption and long-term use.

References

[1] Tilde M. Bekker and Berry H. Eggen. 2008. Designing for children's physical play. In *CHI '08 Extended Abstracts on Human Factors in Computing Systems*. ACM, Florence Italy, 2871–2876. doi:10.1145/1358628.1358776

[2] Boudewijn Boon, Marco Rozendaal, Marry M. van den Heuvel-Eibrink, Janjaap van der Net, and Pieter Jan Stappers. 2016. Playscapes: a Design Perspective on Young Children's Physical Play. In *Proceedings of the The 15th International Conference on Interaction Design and Children (IDC '16)*. Association for Computing Machinery, New York, NY, USA, 181–189. doi:10.1145/2930674.2930713

[3] John A. Byers and Curt Walker. 1995. Refining the Motor Training Hypothesis for the Evolution of Play. *The American Naturalist* (July 1995). doi:10.1086/285785 Publisher: University of Chicago Press.

[4] Fernanda De La Torre, Cathy Mengying Fang, Han Huang, Andrzej Banburski-Fahey, Judith Amores Fernandez, and Jaron Lanier. 2024. LLMR: Real-time Prompting of Interactive Worlds using Large Language Models. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. ACM, Honolulu HI USA, 1–22. doi:10.1145/3613904.3642579

[5] Linda de Valk, View Profile, Tilde Bekker, View Profile, Berry Eggen, and View Profile. 2013. Leaving room for improvisation. *Proceedings of the 12th International Conference on Interaction Design and Children* (June 2013), 92–101. doi:10.1145/2485760.2485771

[6] Sam Earle, Samyak Parajuli, and Andrzej Banburski-Fahey. 2025. DreamGarden: A Designer Assistant for Growing Games from a Single Prompt. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. ACM, Yokohama Japan, 1–19. doi:10.1145/3706598.3714233

[7] Maxence Faldor, Jenny Zhang, Antoine Cully, and Jeff Clune. 2025. OMNI-EPIC: Open-endedness via Models of human Notions of Interestingness with Environments Programmed in Code. doi:10.48550/arXiv.2405.15568 arXiv:2405.15568 [cs].

[8] Mahdi Farrokhi Maleki and Richard Zhao. 2024. Procedural Content Generation in Games: A Survey with Insights on Emerging LLM Integration. *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment* 20, 1 (Nov. 2024), 167–178. doi:10.1609/aiide.v20i1.31877

[9] Jiaying Fu, Xiruo Wang, Kate Vi, Zhouyi Li, Chuyan Xu, and Yuqian Sun. 2025. "I Like Your Story!": A Co-Creative Story-Crafting Game with a Persona-Driven Character Based on Generative AI. In *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. ACM, Yokohama Japan, 1–5. doi:10.1145/3706599.3721163

[10] Roland Graf, Pallavi Benawri, Amy E. Whitesall, Dashiell Carichner, Zixuan Li, Michael Nebeling, and Hun Seok Kim. 2019. iGYM: An Interactive Floor Projection System for Inclusive Exergame Environments. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. ACM, Barcelona Spain, 31–43. doi:10.1145/3311350.3347161

[11] Roland Graf and Surat Kwanmuang. 2015. Solar Pink Pong: Street Video Game. In *Proceedings of the Ninth International Conference on Tangible, Embedded, and Embodied Interaction*. ACM, Stanford California USA, 417–418. doi:10.1145/2677199.2690877

[12] Mengyan Guo, Jun Hu, and Steven Vos. 2024. TIDAL: exploring the potential of data physicalization-based interactive environment on runners' motivation. *Journal of Ambient Intelligence and Humanized Computing* 15, 4 (April 2024), 2425–2438. doi:10.1007/s12652-024-04762-6

[13] Brett A. Halperin and Stephanie M Lukin. 2024. Artificial Dreams: Surreal Visual Storytelling as Inquiry Into AI 'Hallucination'. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference* (Copenhagen, Denmark) *(DIS '24)*. Association for Computing Machinery, New York, NY, USA, 619–637. doi:10.1145/3643834.3660685

[14] B Hughes. 2006. A Playworker's Taxonomy of Play Types, Play Education. *London: Playlink* (2006).

[15] Hongfei Ji, Yuhan Yuan, and Qiao Jin. 2025. "Jump, Stop, Jump Again": Exploring AI-Supported Physical Activity Play at Home with Parents and Children. In *Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play (CHI PLAY Companion '25)*. Association for Computing Machinery, New York, NY, USA, 215–221. doi:10.1145/3744736.3749349

[16] Brett Jones, Rajinder Sodhi, Michael Murdock, Ravish Mehra, Hrvoje Benko, Andrew Wilson, Eyal Ofek, Blair MacIntyre, Nikunj Raghuvanshi, and Lior Shapira. 2014. RoomAlive: magical experiences enabled by scalable, adaptive projector-camera units. In *Proceedings of the 27th annual ACM symposium on User interface software and technology*. ACM, Honolulu Hawaii USA, 637–644. doi:10.1145/2642918.2647383

[17] Jungmin Lee, Seoyoung Yoon, Hwajin Shim, and Youngjae Yoo. 2025. Development of an LLM-Based Chatbot to Support Learnability in Stardew Valley: A Diary Study Approach. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 1070, 19 pages. doi:10.1145/3706598.3713310

[18] Chris Elvis Leisi and Ulrich Götz. 2024. Virtual Real Spaces: In-Home Gaming Experiences Bridging Reality and Virtuality. In *Companion Proceedings of the 2024 Annual Symposium on Computer-Human Interaction in Play*. ACM, Tampere Finland, 157–162. doi:10.1145/3665463.3678812

[19] Qingchuan Li and Simin Yang. 2024. Experiencing the body as play: Cultivating older adults' exergame experiences using embodied metaphors and multimodal feedback. *Computers in Human Behavior* 158 (Sept. 2024), 108280. doi:10.1016/j.chb.2024.108280

[20] Danica Mast, Michel Bosman, Sylvia Schipper, and Sanne De Vries. 2017. BalanSAR: Using Spatial Augmented Reality to Train Children's Balancing Skills in Physical Education. In *Proceedings of the Eleventh International Conference on Tangible, Embedded, and Embodied Interaction*. ACM, Yokohama Japan, 625–631. doi:10.1145/3024969.3025085

[21] Louise Petersen Matjeka. 2020. The Move Maker - Exploring Bodily Preconditions and Surrounding Conditions for Bodily Interactive Play. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. ACM, Honolulu HI USA, 1–6. doi:10.1145/3334480.3381652

[22] Louise Petersen Matjeka and Florian 'Floyd' Mueller. 2020. Designing for Bodily Play Experiences Based on Danish Linguistic Connotations of "Playing a Game". In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. ACM, Virtual Event Canada, 19–31. doi:10.1145/3410404.3414264

[23] Louise Petersen Matjeka, Dag Svanæs, and Alf Inge Wang. 2022. Turning Eight Family Homes Into Interactive, Pervasive Playgrounds During the COVID-19 Pandemic Lockdown. *Frontiers in Computer Science* 4 (May 2022). doi:10.3389/fcomp.2022.822337

[24] Markus Montola, Jaakko Stenros, and Annika Waern. 2009. *Pervasive games: theory and design*. CRC Press.

[25] Elena Márquez Segura, Annika Waern, Jin Moen, and Carolina Johansson. 2013. The design space of body games: technological, physical, and social design. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, Paris France, 3365–3374. doi:10.1145/2470654.2466461

[26] Anthony D Pellegrini and Peter K Smith. 1998. Physical activity play: The nature and function of a neglected aspect of play. *Child development* 69, 3 (1998), 577–598.

[27] Sara Price and Yvonne Rogers. 2004. Let's get physical: The learning benefits of interacting in digitally augmented physical spaces. *Computers & Education* 43, 1 (Aug. 2004), 137–151. doi:10.1016/j.compedu.2003.12.009

[28] Richard S Strauss, Daria Rodzilsky, Gail Burack, and Michelle Colin. 2001. Psychosocial correlates of physical activity in healthy children. *Archives of pediatrics & adolescent medicine* 155, 8 (2001), 897–902.

[29] Maya Grace Torii, Takahito Murakami, and Yoichi Ochiai. 2023. Lottery and Sprint: Generate a Board Game with Design Sprint Method on AutoGPT. In *Companion Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. ACM, Stratford ON Canada, 259–265. doi:10.1145/3573382.3623706

[30] Loes Van Renswouw, Jelle Neerhof, Steven Vos, Pieter Van Wesemael, and Carine Lallemand. 2021. Sensation: Sonifying the Urban Running Experience. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. ACM, Yokohama Japan, 1–5. doi:10.1145/3411763.3451788

[31] Margaret Whitehead. 2001. The concept of physical literacy. *European Journal of Physical Education* 6, 2 (2001), 127–138.