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Active Project: Supporting Young Children's Computational Thinking Skills Using a Mixed-Reality Environment

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Supporting Young Children's Computational Thinking Skills Using a Mixed-Reality Environment

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Abstract

The purpose of this study was to develop a mixed-reality environment for supporting young children's computational thinking skills and evaluate the feasibility of this system for further research steps. Seventeen young children aged from six to eleven participated in the study by using the augmented reality technologies and interacting with a social robot while solving the path-finding problem. The motion capture sensors were utilized to precisely capture individual kids' behavior. We found that individual kid's learning progress dramatically improved after experiencing a few trials, and this improvement was more apparent in the 6 to 8 years old children group compared to 9 to 11 years old group. In addition, multimodal data visualization allowed us to assess the in-depth analysis of the event when each kid struggled to solve the problem. Future study would evaluate the effectiveness of this system by comparing the intervention group and control group after a prolonged week exposure.

1. Introduction

According to the National Science Board [1], by 2026, the number of jobs that require STEM skills will grow consistently, but the U.S. K-12 mathematics and science performance has been stagnant, remaining well below many other countries. This report also points out that the underrepresentation of gender and ethnic minorities in the STEM workforce is still problematic. Furthermore, the COVID-19 pandemic has increased the challenge of equitable development of young STEM talents to unprecedented levels. Due to the shelter-in-place rule, online technology has been used ever more broadly for both education and work. Yet, the Northwest Evaluation Association [2] projects the academic growth of children of all ages will be severely impaired, with greater severity in mathematics than reading. Expectedly, this impact will be more detrimental to younger children in elementary school than secondary and for children of color and children coming from low income families [3].

For young children, online learning as is currently implemented might not be sufficient. Both principals and teachers have identified that the greatest need is for resources that will engage children in learner-centered, hands-on activities and will facilitate social and emotional learning [4]. Children's interaction with tools and others around them is fundamentally multisensory and multimodal [5]. Optimal STEM learning environments should support this natural multimodal way of interaction, engaging children not only cognitively but also social-emotionally and physically [6]. Also, positive experiences in STEM-related tasks at an early age lead to the development of a positive STEM identity [7], which will serve as a catalyst for the STEM pipeline. It is necessary and urgent to investigate creative approaches to the use of cutting-edge technologies to provide all children with developmentally appropriate and equitable STEM learning opportunities, regardless of their real-life conditions.

The project team envisioned that every child would come to identify technologies as useful tools for their play, learning, and lives, and grow competent as producers and proficient users of advanced technology [8]. To this end, emerging technologies could be combined innovatively to provide an optimal STEM environment for children's personalized learning. Young children demonstrate sustained engagement voluntarily with digital virtual characters and robots and even develop social relationships with them [9].

This study aimed to provide an innovative mixed-reality environment that would combine a physically embodied humanoid robot and augmented reality (AR), where children in K-2 would engage in computational tasks embedded in their play with the robot. Through this hands-on experience, children would understand the concepts of sequences and symbols that were crosscutting and foundational to STEM literacy and problem solving. Also, grounded in embodied cognition and culturally responsive/sustainable pedagogy, this environment would invite every child equitably to AR-enhanced play with a robot playmate that was free from judgments and social biases, enabling children's positive affect about working with and on such cutting-edge technologies.

2. Methods

2.1. Mixed-Reality System

The purpose of this study was to develop an innovative mixed-reality environment that supports early development of computational thinking. In this environment, children in K-2 walk around on a 5x5 chessboard-like grid on a floor mat to help a robot (*Linibot*) find a path toward a goal while holding a tablet. The robot guided children with instructions, cues, and corrective and motivational feedback. The tablet displayed an equivalent map and several AR obstacles for the child to avoid.

The specific learning objectives were foundational STEM problem solving skills including the understanding of symbols and sequences that are crosscutting STEM domains, and developing children's confidence in advanced technology use. Importantly, we unobtrusively assessed children's progresses while they played in the environment by using multimodal behavioral data collection technology such as automated interaction logs capturing their walking path and time taken to the goal and an optical motion capture system to precisely collect bodily gestures. We have been developed the mixed-reality environment iteratively over one and a half years, testing our ongoing designs with twenty-five children in informal settings (our lab, a community center, and a STEM showcase event). Each test has had a different focus dependent on the developmental progress of the environment.

2.2.Procedures

Seventeen boys and girls were recruited for one-on-one in a local one-day STEM showcase event. The children were aged six to eleven, and their ethnicities included Caucasian, Asian, and African American. The parents and children voluntarily walked into our booth. After obtaining parental consent, each child played two episodes of the path-finding game: Game 1 taking five to ten minutes and Game 2 taking ten to twenty minutes. Before playing the game, children wore the motion capture jacket and a hat with the assistance of a research assistant. The motion capture suit was attached by reflective markers to track children's movements during the session. When children approached the game place, a social robot greeted with utterances which was instantly operated by a human operator behind the scene. A social robot expressed encouragement when a kid struggled to finding a next step during the game. Various utterances of a social robot were spontaneously controlled by a human operator. A social robot was also able to move and this was manipulated by a human operator using a tablet controller. A social robot served as a peer, and followed a kid's path without disturbing the kid's task.

2.3. Data Analysis

The data from the interaction logs was used to assess each child's walking path and total distance traveled and time taken to the goal. For each subtask finding a gem, a kid's travel distance and time spend were recorded for each grid cell. The optimal path was separately calculated from the start point to the gem, and this was compared with the actual path of children's approach. Following this, the data from optical motion capture technology was used to compare these two sets of data to understand how the data sets would enable assessing children's learning progresses authentically. Based on reflective markers attached to the children's head and neck, children's tablet, and a social robot, several behavioral measures were computed including the distance between the head centroid to the tablet, distance between the head centroid to a social robot, neck angle, neck angular velocity, and neck displacement. These measures have been used in a previous study to assess children's gestures [10].

3. Results

3.1. Macro assessment of performance

Figure 1 illustrates the trend of the total distance (cm) difference between individual child's actual path and theoretically optimal path. Most children showed lower performance at the early stage of the session. After collecting a few gems, the performance dramatically improved.

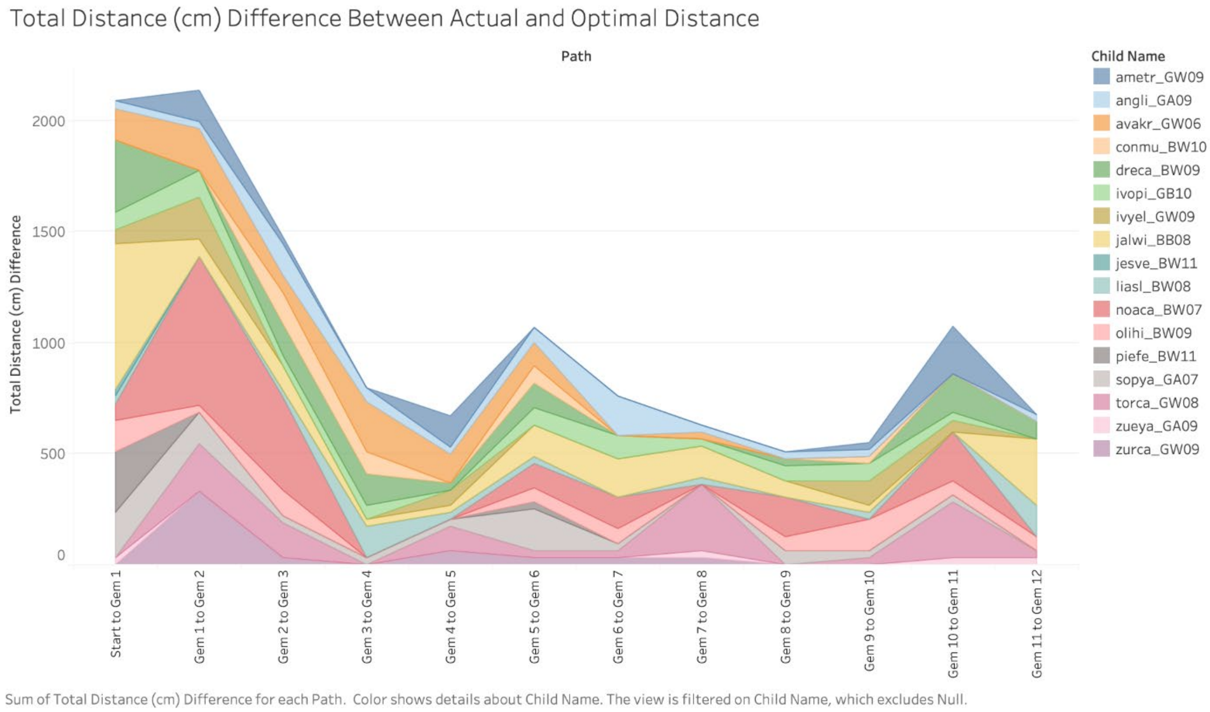

Figure 1. Area chart of total distance difference between actual and optimal path of individual child during mixed-reality learning session.

Further analysis was conducted by different age groups (6 to 8 years and 9 to 11 years), as seen in Figure 2. The performance of the 9 to 11 years old group was higher than 6 to 8 years old group throughout the session. Especially, the older age group did not reveal significant lower performance at early stage of the learning session, which was opposite to younger group.

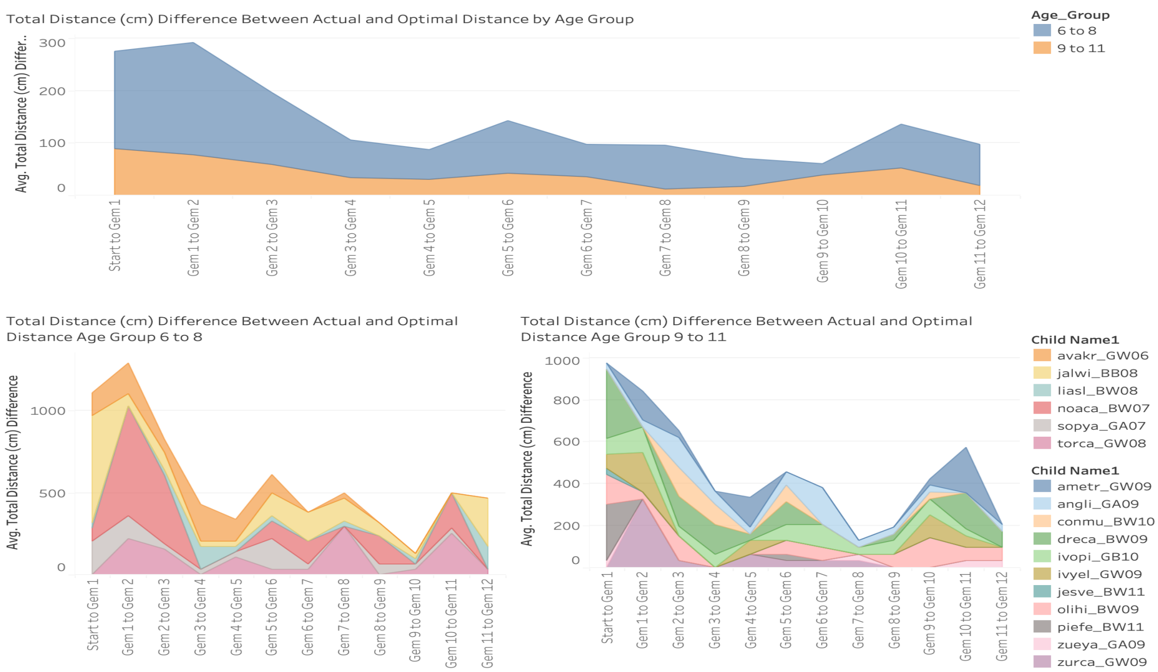

Figure 2. Area chart of total distance difference between actual and optimal path by two different age groups (6 to 8 and 9 to 11).

3.2.Micro assessment of performance

To conduct an in-depth assessment of performance, the comparison between the actual path and optimal path, and the heatmap displaying the time spent for each cell was created, as seen in Figure 3. It helped us to understand individual kid' path-finding strategies and efficiency of their spatial thinking.

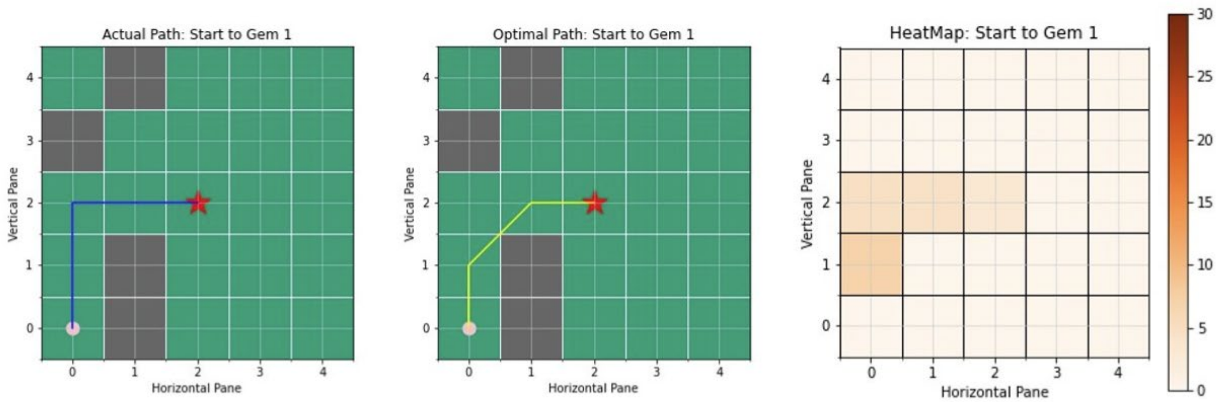

Figure 3. The visualization of the actual path and optimal path, and heatmap of displaying the time spent for each cell. This figure is an example of one kid's one trial finding a gem.

3.3.Bodily movement

To better understand children's bodily movement and behavioral strategies, motion capture-based measures were evaluated, as seen in Figure 4. For example, Kid A's finding gem 2 showed a lower performance compared to the optimal path. Meanwhile, it was observed that Kid A revealed a greater distance from the tablet and a social robot. A kid spent the longest time on the cell highlighted in the Figure 4 to find the location of a gem and decide the next step.

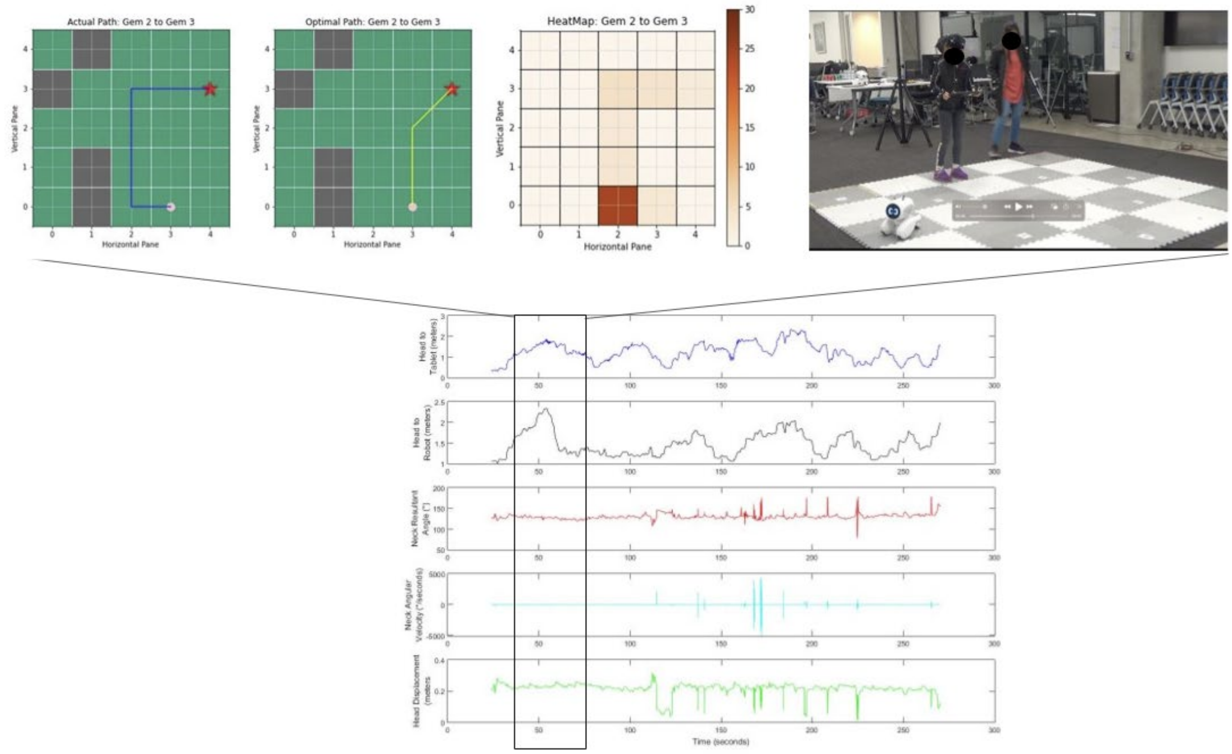

Figure 4. An example of the multimodal assessment of children's learning behavior.

4. Discussion

We studied the feasibility of the mixed-reality learning environment for young children with the aid of multimodal data measurement. We observed that children enjoyed using this new technology and interacted with a social robot while solving the path-finding problem. Our preliminary results showed that children showed lower performance at the early stage but the performance was drastically improved after participating in a few trials. This trend was more apparent for the younger age group (6 to 8 years old). This indicates that the system we developed was intuitive and may enable children's STEM thinking capability for a long term.

Once more data would be collected, the statistical analysis will be conducted to test our hypotheses. We hypothesized that the learning performance would increase over time with the aid of our mixed-reality learning environment. We will employ the one-way ANOVA or Kruskal – Wallis test to determine whether the learning performance would be affected by different time period (e.g., initial vs. middle vs. end). Another hypothesis was that the slope of the learning curve would depend on the age groups. We will conduct the independent t-test or Mann-Whitney U test to compare the learning performance between two different age groups (6 to 8 and 9 to 11).

Embodied cognition theory posits that our cognition is grounded deeply in bodily interactions with our social, cultural, and physical environments [11]. Sensory motor systems (the neural systems processing sensation and perception) are involved in cognition, and cognition is mediated by bodily movements and processes. Considerable evidence has accumulated over the last two decades on the integral role that the body plays in knowledge development and learning [12].

Importantly, embodied cognition dovetails with child development theory that acknowledges the integral nature of intellectual, social, emotional, and sensory-motor development. Six to eight-year-old children are typically developing fine and gross motor skills; therefore, they are rarely able to sit quietly for extended periods. Additionally, their development of visual-motor skills is closely connected to their later success in academic work including mathematics and science [13]. Similarly, in embodied cognition research [14], it was shown that children (aged six to eight) relied on their bodies to reason about the time when reading an analogue clock.

An inclusive environment like our proposed mixed-reality environment therefore could offer every child an opportunity to exploit their personal and cultural resources, or funds of knowledge

[15], while they learn. It also allows a child to have a sense of agency and autonomy to participate in a STEM learning community, voluntarily sharing their interests and assets and enriching the community's capacities.

Notably, AR supports embodied learning experience. An AR-enabled learning environment that mixes physical and virtual realities (i.e., a mixed-reality environment) allows a learner to use his/her body to generate and manipulate relevant ideas that are represented in a digital form and observe vividly how the ideas work in flow. In an AR augmented science learning application, a student (playing the role of an augmented bee) physically navigated to find nectar and communicate with other bee [16]. This was in line with our study's findings. These AR applications are intended to support students' conceptual understanding through experiential learning.

Social (or sociable) robots are physically embodied, life-like robots that interact in a human-like way [9]. Equipped with more advanced features like anthropomorphism, physical embodiment, socio-emotional presence, and mobility [17], a humanoid social robot could induce even stronger relational dynamics with children. In fact, a few review studies on social robotics confirm that children demonstrate highly developed social and affectionate relationships with their physically embodied, social robots [18].

Noteworthy is the use of a social robot to foster inclusive and equitable experiences. Prior research on human/computer interaction showed that adolescent girls and ethnic minorities developed higher self-efficacy in and more positive attitudes toward learning mathematics and perform better when assisted by virtual pedagogical agents, compared to their white male counterparts [19]. These students felt safe trying and made mistakes and felt cared for by the agents’ verbal encouragement free from biases and judgment. A similar phenomenon was observed in our data collection in this present study.

Although this study was carefully designed, there were several limitations. First, the sample size was limited. Given the preliminary test stage, we could not collect a large sample, and a statistical analysis was not conducted due to low statistical power. Second, we did not compare the effectiveness of our proposed system to the control group. The focus of this study was to confirm the readiness of our developed mixed-reality system for the further step. In future study, we would compare the degree of the spatial thinking between the control and intervention groups.

5. Conclusion

This study implemented and tested the feasibility of the mixed-reality learning environment based on embodied cognition theory, social robotics, and AR learning for young children. This advanced technology helped individual kid to play and learn the spatial thinking skills while solving the path-finding tasks with the emotional and social support from a social robot. The motion capture system was able to capture and quantify each kid’s authentic behavior during the learning session. The proposed learning environment would be useful to build young children’s computational thinking skills, and could serve as an useful pedagogical tool enabling teachers’ curriculum.

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