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Research paper

Leveraging eye tracking to understand children's attention during game-based, tangible robotics activities

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ABSTRACT

The difficulty in maintaining attention can interfere with the acquisition of critical academic skills. Recently, researchers have used embodied and game-based learning to support skill acquisition for children with learning difficulties. In this context, robots can be an interesting asset to foster engagement and investigate game dynamics. However, it is still an open question of how to develop adaptive learning environments for children with learning difficulties. Before one can provide effective adaptation, a first step is needed to understand the differentiating behaviors during the activity for children with attention difficulties. Three such differentiating behaviors are how a child divides his or her attention during the learning activity, the child's level of cognitive load, and the child's physiological fatigue, which are the focus of our study Using a robot assisted, gamified activity, we conducted a user study with 18 children having difficulty in maintaining attention. Using process mining techniques and eye-tracking data, we found the importance of integrating the autonomous robots into the attention patterns to successfully complete a game and the influence their behaviors can have on the participant's attention. This importance was supported by the cognitive load of participants decreasing the more they focused on the autonomous robots in successful games. This work contributes to the understanding of children's behaviors during tangible game-based activities and can be used to build effective adaptation for children with attention difficulties.

1. Introduction

The difficulty in maintaining attention can interfere with the acquisition of critical academic skills that might affect long-term achievement even though the attention problems diminish over time (Rabiner, Carrig, & Dodge, 2016). Students with learning difficulties, such as attention deficit hyperactivity disorder (ADHD), may have difficulty with their working memory, flexibility, time-management, motor-planning and self-control, and organization (Fabiano et al., 2009). Historically, children with attention difficulties typically join extracurricular activities or occupational therapy sessions, including several visio-motor exercise activities, to improve attention as well as to improve coordinated visual and motor skills. A more recent trend in research has focused on the use of embodied and game-based learning to support skill acquisition for children with learning difficulties (Boccanfuso et al., 2016). In this paper, we combine embodied and game-based learning in a tangible, robotic Pacman game to support children with learning difficulties in practicing attention and motor skills. Particularly, we are interested in the attention and cognitive behaviors that the children exhibit while engaged in this activity and can be captured through eye tracking. This work provides insights that can be used to inform the development of more adaptive support in future systems.

Across learning paradigms, adaptation is often key to providing the right support at the right time. Particularly, personalizing play activities to children's preferences (Boccanfuso et al., 2016) or game difficulties (Schadenberg, Neerincx, Cnossen, & Looije, 2017) is an efficient way to keep users engaged when playing with a robot. Activities should not just adapt over time but should be adjustable to the child's abilities and problem task (de Greef, Van der Spek, & Bekker, 2013). However, to provide effective adaptation, a first step is needed to understand the differentiating behaviors during the activity to understand what occurs during the game play and where the opportunities are for adaptation.

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In this study, 18 children with a range of attention related difficulties worked with a low cost, easy to use, gamified robot assisted tangible Pacman activity to support attention and visio-motor integration. In other words, the children played a physical Pacman game in which both the two ghosts and one Pacman were robots on a paper map. The children had to control the Pacman to collect six apples across the map without getting caught by the ghosts or they had to start the game-play over. To understand the children's attention and cognitive patterns, we collected eye-tracking data as the children engaged with the robot-enhanced game. Using this eye-tracking data, we investigated three research questions to better understand how the children were engaging with the system. First, **(R1) how do the participants' processes, as indicated by their gaze fixation patterns, change between unsuccessful and successful games (game success) and easy and hard games (game difficulty)?** Particularly, we are interested in how the participants' attention to the robots fit into their game-play process and how the robot ghosts' speeds influenced these attention measures. Second, **(R2) how does a participant's cognitive load correlate with game success and game difficulty, and (R3) how does a participant's physiological fatigue correlate with game success and game difficulty?** Our work contributes to the understanding of the role attention plays in educational robotics games and how changes in robot behaviors can influence the learning process as captured through eye-tracking patterns. We believe that investigating the attention towards game components and exploring the relationship between gaze behavior and game performance lead us to implement more sophisticated and adaptive games that can account for behaviors of children with learning disabilities rather than only supporting neuro-typical children.

2. Related work

2.1. Embodied, game-based learning

Embodied cognition highlights the usefulness of the connection between body and mind, and its relation with surrounding environment while learning and/or problem solving (Wilson, 2002). The embodied learning theory is based on the idea that brain and body have an inseparable link that supports them in working together (McClelland, Pitt, & Stein, 2015). In this way, the physical body can play a role in the cognitive process.

Embodied learning has had positive impacts on children's short-term memory skills and emotional stages (Kosmas, Ioannou, & Retalis, 2018) as well as improvements to children's motor performance (Kosmas, Ioannou, & Retalis, 2017). Previous literature has shown considerable confidence in the tools developed based on the design principles of embodied learning (Hsu, 2011). Furthermore, it has been shown that the children with special educational needs and their family members/teachers/caregivers/therapists consider such tools beneficial for learning (Bartoli, Garzotto, Gelsomini, Oliveto, & Valoriani, 2014; Edwards, Jeffrey, May, Rinehart, & Barnett, 2017; Kourakli et al., 2017; Malinverni, Mora, Padillo, Hervas, & Pares, 2014) and consider such interventions as possible options for classroom integration (Kourakli et al., 2017).

Researchers often have combined these embodied learning interventions with game-based elements. Qian and Clark (2016) found that game-based learning approaches may be effective in helping students develop their 21st century skills. By providing an engaging environment, children can improve their attention skills during a game-based activity (Cassar & Jang, 2010). Furthermore, these types of activities can improve memory, concentration, motor planning and time management skills (Frutos-Pascual, Zapirain, & Zorrilla, 2014). Many embodied games are developed using Kinect and Wii technology (Kosmas et al., 2017, 2018), but robots can also be an interesting asset to foster engagement and investigate game dynamics. For example, Boccanfuso et al. (2016) presented a study in which children with or without Autism Spectrum Disorder (ASD) played with a Sphero robot. The child–robot interaction patterns were analyzed and revealed specific patterns discriminating children with ASD from others. Through the use of robots, a child can still engage in a tangible activity through the control of a robot while also having the possibility of extending the game space using autonomous robots with which the child can interact. Although, as discussed above, these embodied learning interventions have supported children with a range of needs, the adaptation of the system to support this variability of needs is lacking in the literature. In this work, we investigate how gaze patterns and robotics log could be use to distinguish patterns that could be then integrated into an adaptive system.

2.2. Robot-assisted motor learning

Motor skills deal with both movements and cognitive processes allowing motion of body parts in space. While gross motor skills involve large body muscles and pertain to balance orientation of movement of trunk, limbs and posture, fine motor skills involved coordination of small muscles for tasks like drawing or writing (Cameron, Cottone, Murrah, & Grissmer, 2016). Gross motor skills are a critical part of children's developing social competencies and physical well-being and are a gateway to engagement in learning and social activities, including sports and games, throughout the school years (Pagani & Messier, 2012; Wilson, Piek, & Kane, 2013).

Cameron et al. (2016) highlighted three cognitive processes that are usually targeted when evaluating motor skills: (1) Motor Coordination, (2) Executive Function and (3) Visuospatial Skills. **Motor Coordination** involves motor planning and spatial sequencing. **Executive Function** is defined by a set of cognitive processes that helps children focus and shift their attention, manipulate information in working memory, and inhibit maladaptive responses to meet adaptive goals (Cameron et al., 2016). When performing motor actions, children must maintain their attention to the task, whether sorting manipulatives or organizing learning materials. **Visuospatial Skills** involve perceiving spatial relations, visualizing objects using cognitive representations in 2D or 3D space, and manipulating those representations.

Among technologies used to help motor and attention learning, we found that robots have been of interest in the past few years. Through their abilities to easily perform the same sequences of actions over and over, robots are particularly suitable for repetitive training. For example, several studies have used social robots to play imitation games with participants (Guneysu, Siyli, & Salah, 2014; Malik, Yussof, & Hanapiah, 2014; Matarić, Eriksson, Feil-Seifer, & Winstein, 2007). Some other studies used tabletop robots such as Guneysu Ozgur et al. (2020), who proposed the design of a robot-assisted handwriting activity for children with handwriting difficulties. In the same handwriting context, Lemaignan et al. (2016) showed how a social robot could engage children for long training periods.

A crucial point mentioned by the authors of these studies is the adaptation of the task difficulties to the skills of the participants. This adaptation, just like in any game, needs to be accurate in order to keep the user challenged but not frustrated (Yannakakis & Hallam, 2009). In previous social robots for learning studies, authors have proposed to estimate the child's engagement in the task using attention tracking (Johal, Jacq, Paiva, & Dillenbourg, 2016; Lemaignan, Garcia, Jacq and Dillenbourg, 2016). However, eye-tracking data could also be used to estimate other interesting metrics for adaptation in robot-mediated training for example, attention distribution (Chen, Wang, Peng, Yan, & Pan, 2019; Gallagher & Byrne, 2013; Palinko, Rea, Sandini, & Sciutti, 2016), joint attention (Bekele, Crittendon, Swanson, Sarkar, & Warren, 2014) and target selection performance (Bekele et al., 2013).

2.3. Assessing attention using eye-tracking

Previous research has shown the effectiveness of eye-tracking in differentiating expertise levels, problem difficulty and task-based performance. For example, gaze behaviors can indicate when participants are unable to solve problems providing insights into the problem-solving process (Knoblich, Ohlsson, & Raney, 2001). Moreover, researchers have found gaze patterns can be used to differentiate expert and novice problem solvers across domains (Grant & Spivey, 2003; Reingold, Charness, Pomplun, & Stampe, 2001; Thomas & Lleras, 2007). Many of these studies have focused on differentiating between *what* expert/high-performers and novices/low-performers look at and for *how long*. This same type of analysis has been used during game play to differentiate between players by analyzing their length of fixations (Frutos-Pascual & Garcia-Zapirain, 2015; Renshaw, Stevens, & Denton, 2009). However, in many learning tasks, including those involving educational robots, it is as important to consider temporal aspects of these gaze patterns as we do in this paper. To better understand the problem-solving process, we can assess how participants transition between these different gaze events. In addition to assessing gaze patterns to investigate attention, cognitive load, which can be computed through pupillary activity gathered from eye-tracking, can be used to gauge the mental effort related to a problem. Mental effort becomes important when we consider task difficulty as tasks that do not take much effort may lead to participants losing focus. Previous work has shown that gaze-based indicators of the cognitive load successfully differentiate the different difficulty levels of the respective tasks (Harbluk, Noy, Trbovich, & Eizenman, 2007; Kaller, Rahm, Bolkenius, & Unterrainer, 2009). By understanding the amount of effort that a participant is exerting, we can better understand how they are perceiving the robotic environment.

As can be seen through the relationship between difficulty and cognitive load, differences do not just occur between participants, but the gaze patterns can be manipulated through adaptations in the system. For example, adaptive hints given during educational games not only increase the performance of the students but also the degree to which the players pay attention to the hints (Conati, Jaques, & Muir, 2013). Similarly, researchers have used interactive eye tracking to develop initial prototypes of automated tools which could help young children (toddlers and pre-teen) with atypical visual attention to not only attend to social information in a more typical manner, but also to internalize it (Wang et al., 2015). Furthermore, eyetracking has also been used as an input modality in the games for behavioral therapy (Al-Shathri, Al-Wabil, & Al-Ohali, 2013). When robots are used to support learning, adaptation is a key factor and it is important to understand how the changes in robot behavior influence the participant's attention.

3. Robotics system overview

3.1. Robotic platform

Our study was designed using the Cellulo robotic platform (Özgür, 2018). The Cellulo robotic platform is composed of small-sized, graspable and haptic-enabled robots, paper sheets as a game space, and a controller application run on a tablet, a computer, or an android phone. The paper sheets include both visual information for the participant and the Cellulo robot. The paper sheet has a visual design of the workspace/gamespace within which the participant interacts. Furthermore, the sheets contain a small dot pattern that allows the Cellulo robots to operate on these printed papers and to localize themselves with sub-mm accuracy (Hostettler, Özgür, Lemaignan, Dillenbourg, & Mondada, 2016). This accurate localization allows one to monitor the user's motion through the robot being held.

The robots can be used as an interface for interacting with many virtual point-like objects that reside on this 2D plane (Özgür, 2018). The original design objective of the Cellulo robotic platform is to provide a practical, easy to use and intuitive interface for ranging human–robot interaction scenarios within home and school environments. Researchers have used them as a passive, semi-passive or active agents within educational (Neto et al., 2020) and therapeutic activities (Guneysu Ozgurm, Özgür et al., 2020; Guneysu Ozgur, Wessel et al., 2020) in schools, occupational therapy centers, home environments, and hospitals.

3.2. Tangible pacman game

In this study, our participants engaged with a tangible Pacman game designed to support motor learning (Guneysu Ozgur et al., 2018). The tangible Pacman game was iteratively designed with patients in various therapy centers. It was tested with healthy children as well as children having some physical or visio-motor coordination issues (Guneysu Ozgur et al., 2018). The game consists of three Cellulo robots including one called Pacman, which is a robot that is manipulated by the player to collect six target apples on a printed paper maze (see Fig. 1. The other two robots are called ghosts and are autonomously chasing the Pacman robot using a shortest path algorithm. If an autonomous ghost robot catches the Pacman robot, the player looses all previously collected apples and the game restarts. An increase in the speed of the ghosts increases the game difficulty. The game also consists of a penalty rule where if the player crashes into a wall of the maze, the last eaten apple is lost as a penalty of that crash. The goal of the game is to collect the all apples as soon as possible while running away from the ghosts and not crashing into the walls. The game ends when the player collects all of the apples. Therefore, for a successful game play, the player has to be attentive to the ghosts' positions, target positions, and where the Pacman is relative to the walls. In this study, an unsuccessful game is when the Pacman gets caught by a ghost while a successful game is when the player collects all six targets.

In this study, all game parameters remained constant across the games except for the speed of the ghost robots. As the speed of the ghost robots increased, the game became more difficult because the participant had to move faster while still maintaining accuracy on the paths to balance not getting caught and not crashing into a wall. As a threshold, easy games were those with a speed under 100 mm/s and hard games were those with a speed over 100 mm/s. A single maze (980 mm $\times$ 420 mm) was used for the Pacman game (Fig. 1). An easy game has the speed of the ghosts set to either 50/60 mm/s or 80 mm/s and a hard game has the speed set to 120 mm/s or 160 mm/s. Further, all games had two ghosts chasing the Pacman. Finally, the Pacman robot provided haptic informative feedback towards the middle of the path when the participant crashed into a wall and they lost an apple. The haptic feedback provided was a short vibration of the robot.

The Pacman game demands visual attention, and the physical motion that takes place during the game play requires visio-motor coordination. Due to the nature of the game, therapists and teachers suggested to use the game as a visio-motor coordination exercise to improve attention as well as visual motor integration. Visual motor integration is the task of interpreting visual information and responding with a motor action (Beery, 2004).

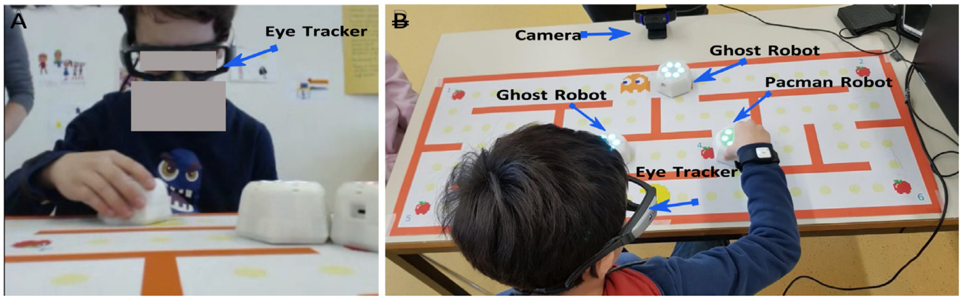

Fig. 1. (A) Experimental set up from the front view through the camera on the table, a participant plays the game on the map while wearing mobile eye trackers. (B) Experimental set up from the back view with a camera facing towards the participant, the participant wears an eye tracker while playing the game by manipulating the Pacman robot in order to collect the apple targets and autonomous ghost robots chase the Pacman (user's robot).

4. Methods

4.1. Participants and experimental design

In our study, 18 children participated. We recruited children 8–11 years old through a partnering school in Switzerland. We got the appropriate ethical approval for the study from Ecole Polytechnique Federale de Lausanne, Switzerland. We also got consent from the school's principal and teachers. Parents and children gave written informed consent prior to the study. All children were given the option of withdrawing from the activity at any time and were explicitly asked after each game if they wanted to continue. All students were exposed to the same game-play configurations. All of our participants had difficulty in maintaining attention and concentration. As is common with attention and concentration difficulties, some children also had a range of other difficulties such as ADHD, Asperger syndrome, poor emotion control, poor anger management, poor working memory or language difficulties. With this range of difficulties, no one child had the same set of difficulties as another, preventing groupings. Rather, we considered all the children to have attention and concentration difficulties with other difficulties being individual differences that allowed us to test the robustness of our analysis across a heterogeneous population. Given the heterogeneity of the population, as a first analysis, we aimed to observe trends within the group. In other words, our goal was not to find how these children are different than a control group. Instead, we wanted to investigate the behavioral patterns of children with attention and concentration difficulties regardless of other difficulties that they may have.

For our study, all participants engaged in the same study design. Before the game play, the game and rules were explained to the participants. No further training was done beyond this explanation. The participants were then asked if they wanted to play the game. At this point, if any child said no, they were excluded from the study. Otherwise, the participant was equipped with mobile eye-tracking glasses that were calibrated before the game play. After the calibration, the participant began playing the game. After the completion of a game, a new game was started unless the participant did not want to continue. Each participant completed a different number of games (M: 3.88,SD: 0.86) as each game was a variable length of time depending on how long it took the child to collect all of the apples and each session was the same length.

Before each new game, the participant was asked if they wanted the ghosts to move faster or to go at the same speed as a motivational technique to give them agency over the game play. The ghosts started at a speed of 50 or 60 mm/s. The speed increases then moved to 80, 120, and 160 mm/s. The participants were not able to reduce the speed of the ghost robots after they moved to a faster speed. All of the participants wanted a higher speed after the initial game except one who instead increased the speed after the second game. At the end of the second game, all participants increased the speed as well. Although the students may have chosen a faster speed, pushing the game beyond their limits, we did not see this in the data where any of the students could not complete the game at a given speed. The minimum number of games played by a child is 2 and the maximum number of games played by a child is. The mean duration of the games was 22.95 s ($SD = 9.16$ s).

4.2. Data collection

We collected the eye-tracking data through SMI eye-tracking glasses with a sample rate of 120 Hz. Despite the difficulty of using eye trackers with children, the tracking accuracy ratios for all of our participants fell between 87.9 and 100%, meaning we had very little loss of data during our collection. However, one participant was removed from analysis due to the eye tracker not fitting correctly and data not being collected for this participant. From the eye-tracking data, we were able to extract gaze behaviors, cognitive load, and physiological fatigue, which we will discuss in more detail in the next section.

In addition to eye-tracking data, data was collected from the Cellulo robot. Specifically, logs collected the start and end time of each game, if the game ended unsuccessfully, and the location of the Pacman robot, x(mm) and y(mm), during the game. The Cellulo robot recorded its position at 93 Hz. Additionally, for each game, we recorded the configuration of the game. We labeled games set to 50, 60 or 80 as easy and all other games as difficult. Any portion of a game that ended in the Pacman robot getting caught, we labeled as unsuccessful, and any game that ended when all fix targets were reached, we labeled as successful.

4.3. Computing eye-tracking measurements

Fixations, Saccades, and Areas of Interest When we consider gaze patterns, there are two types of actions in which a person can be engaged. When a person pauses and focuses on an item in the environment, we consider that a fixation (Salvucci & Goldberg, 2000). On the other hand, the rapid movement that occurs between these fixations are known as saccades. In terms of attention, people look towards and fixate on the object that they are attending to or trying to gain more information about. In this case, we can consider the area that a person is fixated on to be an area that they are attending to with changes in fixations occurring during periods of measured saccades. In this work, we measured moments of fixations and saccades using the algorithms within the SMI BeGaze software (Instruments, 2015).

For the fixations, we were not only interested in whether our participants were attending to an area of the game and for how long, but we were interested in what component of that

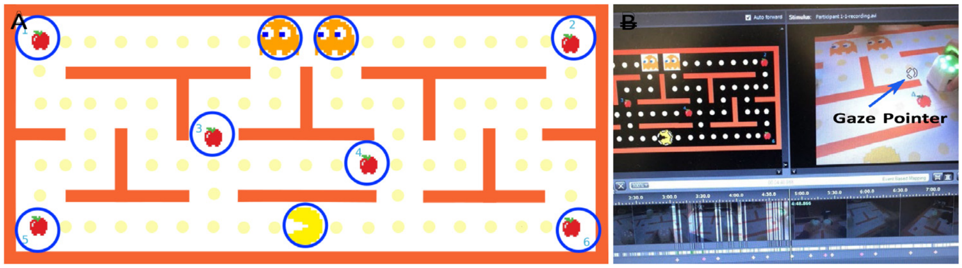

Fig. 2. (A) The Pacman map used in the game with 6 targets (apples) and the visuals indicating initial positions of Pacman and Ghost robots at the game start. (B) BeGaze software used for annotation of gaze data, on the left side, areas of interest on the map can be indicated manually while observing the current eye gaze from the video frame on the right side. In the bottom part the annotator can select the current frame of the video.

game that might be. Specifically, given the game design, we were interested when the participants were attending to their own Pacman robot, the ghost robots, or a target. These components are known as Areas of Interest (AOIs) for our activity design. For each period of fixation, we used the BeGaze software to label the fixation period as Ghost, Target or Pacman, aligning with what the participant was fixated on (see Fig. 2). All other areas were considered Other. All of these labels were completed by a human coder with all of the labels reviewed by a second coder. If disagreement was found, the label was discussed to find agreement. As components of the game moved throughout the game play the AOIs for the Pacman and ghosts moved throughout the board. Given the length of the average fixation and the speed at which the robots moved, this did not impact the classification of a fixation and a saccade. From BeGaze, we were able to export the data at the fixation and saccade level with the associated labels.

Cognitive load Cognitive load is related to the mental effort invested to solve a given problem. We can compute eye-tracking cognitive load as a function of the pupillary activity (Duchowski et al., 2018). There exist other methods of assessing cognitive load from participants. Methods like post-hoc self-reports of cognitive load (Kaiser et al., 2016; Paas, Tuovinen, Tabbers, & Van Gerven, 2003) and NASA task load index (NASA-TLX) (Hart & Staveland, 1988) have an innate limitation of not occurring in real-time (Prieto, Sharma, Kidzinski, & Dillenbourg, 2017). Below we provide the steps for computing cognitive load for each game. The complete details can be found in Duchowski et al. (2018).

1. Compute the 2-level Discrete Wavelet Transform (DWT) of the pupil diameter using the *symlet-16* wavelets.[1]
2. Normalize the second-level detail output of the DWT.
3. Detect the local maxima for each 3-tuple of points.
4. Threshold the series of maxima using the standard deviation of the noise in the signal after removing the maxima.
5. Count the non-zero points and divide by the duration of the game.

Physiological fatigue Physiological fatigue is related to the physical tiredness of the participant. It is computed as the number of blinks per second. The higher the blink frequency is, the higher the fatigue (Schleicher, Galley, Briest, & Galley, 2008; Stern, Boyer, & Schroeder, 1994). The default algorithm from SMI ETG was used to detect the blinks that is based on the difference of the images as shown in Fig. 3. It is a temporal algorithm that used following three steps: (1) detect the eye in the image (this step is highly accurate because the camera is very close to the eye, on the frame of the ETG); (2) find the white part of the eye; (3) determine if the white part of the eyes has an area less than a threshold for a certain duration (blink duration).

Fig. 3. Top left: opened eye, top right: closed eye, bottom left: difference image, bottom right: thresholded difference image.

4.4. Analysis techniques to assess attention differences

As with human-to-human interactions, when interacting with robots, it is not just about where your attention lies but the pattern of events. To capture the attention behaviors of the participants as they engaged with the robotics system, we applied a methodology known as process mining to our fixation data.

Process mining is a temporal analysis technique that builds on the notion of a process model (Bannert, Reimann, & Sonnenberg, 2014). Process models capture the sequences of events and how they follow one another to generate a process (Reimann, 2009). Process mining is a type of data mining (Romero, Ventura, Pechenizkiy, & Baker, 2010) that can help to identify process models through a datacentered approach. In education, process mining is increasingly used to capture differences in students' learning processes (Reimann & Yacef, 2013; Trcka, Pechenizkiy, & van der Aalst, 2010) and would be beneficial in the field of educational robotics to further investigate how the robot fits into these processes.

To analyze the process patterns during successful and unsuccessful games and easy and hard games, we used the ProM software version 6.10 (Rubin et al., 2007). Using this software, we used Fuzzy Miner (Guñther & Van Der Aalst, 2007; Reimann, 2009) to generate a model for each of our game types. The Fuzzy Miner algorithm produces a transition diagram from a sequence of events. In our case, the events were our four visual AOIs.

The Fuzzy Miner algorithm finds underlying processes from data that appears to be unstructured (Guñther & Van Der Aalst, 2007). Taking in a sequence of events, the algorithm produces a model that consists of a set of nodes (corresponding to the

[1] This is a standard wavelet form that is implemented as one of the basic options in both Python and Matlab signal processing libraries/toolboxes.

event types) and edges (capturing the relationship between these events). The model will not show all nodes and edges, but rather will abstract to create an interpretable model using two metrics: significance and correlation. Significance is measured for both the nodes and edges in the graph and captures the relative importance of the occurrence. In other words, if something occurs more frequently, it is more important. The correlation is only calculated for edges and captures how related two events following each other are. Using these metrics, the model can be simplified. Events that are highly significant will remain. However, events that are less significant will be aggregated if they are highly correlated and abstracted if they are not. A more detailed description of this model can be found in Guñther and Van Der Aalst (2007). In ProM, one can set parameters to specify cutoff values. In this paper we set the node cutoff to .25, the edge cutoff to .2, and the utility ratio, which is the weighted sum of the correlation and significance of the edges, to .75. These values were chosen to align with previous research (Bannert et al., 2014). Keeping these parameters consistent across our produced graphs allows us to compare the processes in our different groupings. For all of the models, we had a log conformance percentage of above 90%. Specifically, the unsuccessful games model was 94.61%, successful games model 93.46%, easy games model 95.71%, and difficult games model 91.74%. The log conformance indicates how many of the events could be replayed given the current model. These conformance metrics indicate that our models accounted for most of the data points in our event sequences and well represent the data.

In addition to the process models, we conducted inferential statistical tests to understand the relationship among cognitive load, physiological stress, gaze on AOIs, game duration, game difficulty, and game success. To analyze the relation between the game difficulty and success, we used a Chi-square test. To analyze the relation among the cognitive load, game duration and game success, we first divided the dataset based on the success levels (unsuccessful or success) and computed the Pearson correlation between the cognitive load and game duration. Similarly, to understand the relation between cognitive load, game difficulty and game duration, we first divided the dataset based on the difficulty levels (easy or hard) and computed the Pearson correlation between the cognitive load and game duration. Similar analyzes were performed to understand the relation between two other sets of measurements: (1) cognitive load, gaze on AOIs (Pacman, Ghost, Target, Other), and game success; (2) physiological stress, game duration and game success.

5. Results

We aimed to investigate the relation between game success, difficulty and the information extracted from the eye-tracking data to address our three research questions. As game difficulty and success would be expected to be correlated, before analyzing the relation between the various game and eye-tracking variables, we checked if there is a relation between the game difficulty and the game success (see Table 1). We observed no significant relation between the game difficulty and the success of the game ($\chi^2 = 0.01$, $p = 0.89$). This allows us to treat the two variables, game success (unsuccessful, successful) and game difficulty (easy, hard) in an independent manner.

Table 1
The counts for the game difficulties and game successes. The numbers in the parentheses are the Chi-square residuals. We can observe that none of the residuals are greater than 1.96 (in magnitude). This indicates that there is no significant relation between game difficulty and success.

		Difficulty	
		Hard	Easy
Success	Unsuccessful	8 (−0.25)	11 (0.16)
	Successful	21 (0.23)	23 (−0.15)

5.1. Game success and difficulty processes

In our study, we first aimed to answer the research questions of (R1) how the participants' processes changed between unsuccessful and successful games and easy and hard games. As a reminder, an unsuccessful game is when the Pacman gets caught by a ghost, compared to a successful game when all six targets are reached. An easy game has the speed of the ghosts set to either 50/60 or 80 and a hard game has the speed set to 120 or 160. For all four cases, we created a process model using the Fuzzy Miner algorithm. For each of the cases, all four nodes, each representing an AOI category, were included in the graph. However, the significance levels changed between the different cases as well as the edges, or the transitions, between these fixation events.

For our first model comparison, we investigated the differences between the unsuccessful and successful games (see Fig. 4). In both sets of games, we see that self loops tended have the highest significance. This result means that participants tended to be looking at an object, have fast eye movements to scan and then return to what they were originally focused on. Some of these self loops can be explained by there being more than one area of the screen labeled as that AOI. For example, there are six targets and two ghosts. In unsuccessful games, we found that Other, or areas of the game that did not include the robots or targets, were central points. Most transitions between AOIs occurred either going to or coming from Other. In other words, participants did not often transition between a target, a ghost robot, and their Pacman robot without first focusing on another area on the board. The exception to this is the edge between Target and Pacman. During an unsuccessful game, the participants would transition between focusing on a target and their Pacman robot.

In contrast, a successful game process was very similar to an unsuccessful game process with two important changes to the edges. First, there was no edge going from Target to Other. Second, there is an added transition from Target to Ghost. This change is edges means that after the participants focused on an target, they would then either focus on a ghost or Pacman, but no longer on other places on the board.

For the easy games, we found that the process model was very similar to that of an unsuccessful game (see Fig. 5). Most of the transitions occurred with Other as an intermediary with the exception of a participant's gaze moving from a target to their Pacman. As with the unsuccessful and successful games, there were also self loops when the participant focused back on the same object after a saccade.

In the difficult games where the ghosts are moving faster, we again see that the types of transitions with the Other AOI are reduced as we had seen with the successful games. In this case, the transitions around the ghosts changed. Rather than having transitions between Ghost and Other, during the difficult games, participants would shift their gaze from the Pacman to the ghost and from the ghost to the target location. We explore these differences further in our discussion section.

5.2. Cognitive load, game duration, success and difficulty

For R2, we investigated how a participant's cognitive load changes throughout their sessions in relation to game success and game difficulty. The number of kids in each bucket varies according to Table 2, this is the reason why the gray area (representing the 95% confidence interval) increases towards higher gameID.

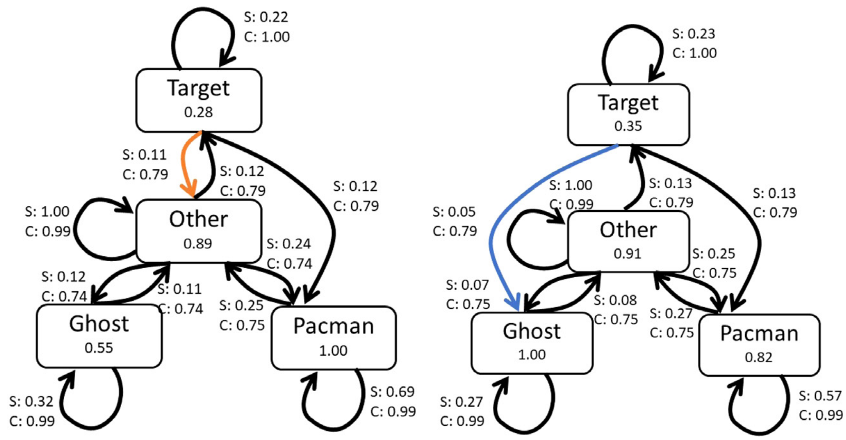

Fig. 4. Process models for unsuccessful games (left) and successful games (right). Each node is labeled with its significance and each edge with its significance (S) and correlation (C). The successful games had more transitions from the Target to the Ghost rather than back to Other compared to the unsuccessful games as seen through the red and blue lines. . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

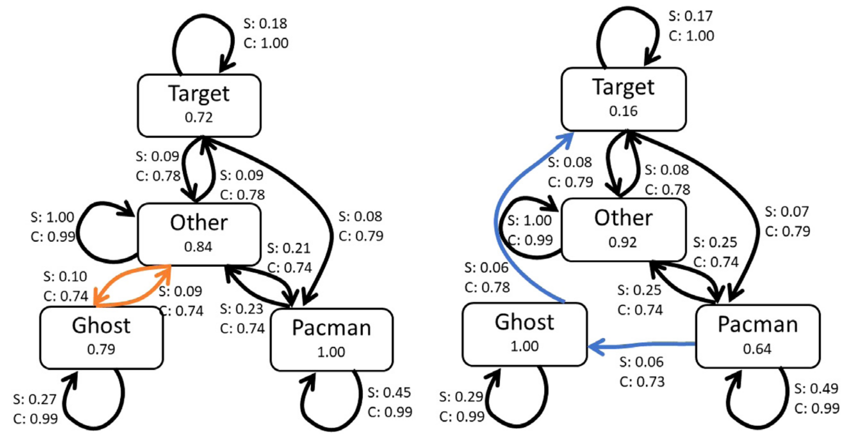

Fig. 5. Process models for easy games (left) and hard games (right). Each node is labeled with its significance and each edge with its significance (S) and correlation (C). The hard games had more transitions from the Ghost to Target and Pacman to Ghost rather than involving Other compared to the easy games as seen through the red and blue lines. . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Number of children and each gameID. The order ID of the games is simply an incremental counter assigned to each game in the order they were played by the children. For example, the first game was given ID "1" and the second game was given an ID "2". The numbering restarted at 1 for every new child.

GameID	1	2	3	4	5	6	7	8	9	10
#Children	18	18	17	16	12	9	7	6	4	3

We observed an interaction effect between the duration of the game, the game success and the timing of the game (the order ID of the game). For the unsuccessful games there is a negative correlation between the duration of the game and when the game was played (Spearman's $\rho = -0.87$, $p = 0.001$). There is no such "linear" relation in the case of successful games. Fig. 6 shows the evolution of game duration for both successful and unsuccessful games based on their IDs. One can observe that for the successful games there is "U-shaped" curve between the game ID and the game duration.

Furthermore, we observed a significant negative correlation between the cognitive load and the duration of the games. The longer the game lasts, the higher a participant's cognitive load gets ($r(90) = -0.20$,$p = 0.04$). Additionally, we observed an interaction effect for the relationship between the cognitive load, game duration and players' success. The negative correlation between the cognitive load and the duration of the games becomes non-significant for the un-successful games ($r(30) = -0.16$, $p = 0.36$); whereas, it becomes stronger for the successful games ($r(58) = -0.26$, $p = 0.04$). Fig. 6 shows the relationship between the three variables. One important observation is that there is a stronger correlation between the cognitive load and the duration of the successful games for the initial games (less than five games, $r(41) = -0.30$, $p = 0.04$). Finally, there is an interaction effect for the relation among the game difficulty, game duration and the cognitive load (Fig. 7). There is a significantly negative correlation between the cognitive load and game duration for the hard games ($r(58) = -0.36$, $p = 0.04$) while there is no significant correlation between cognitive load and the game duration for the easy games ($r(30) = -0.22$, $p = 0.09$). However, when we combine the game difficulty and the game success to analyze the relation between the cognitive load and game duration, we observe that the negative relation is significant only for the successful low difficulty games ($r(21) = -0.43$, $p = 0.03$) while for the other combinations the correlation stays negative but not significant: unsuccessful low difficulty ($r(9) = -0.30$, $p = 0.36$); successful high difficulty ($r(19) = -0.38$, $p = 0.08$); unsuccessful high difficulty ($r(6) = -0.31$, $p = 0.44$).

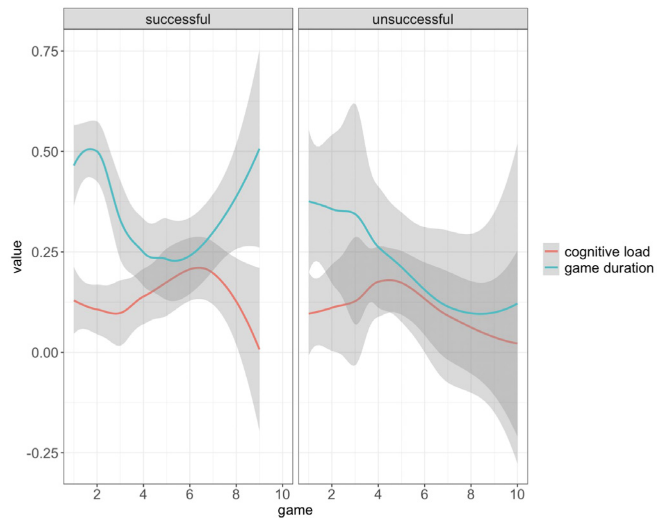

Fig. 6. The evolution of the cognitive load and game duration for the game ID (x-axis). The gray area is the 95% confidence interval. The actual range for the cognitive load is [0–1]. The negative values within the gray area is due to the large confidence interval. Y-axes are normalized between 0 and 1, to save space the Y-axis is plotted between 0 and 0.75. The maximum gameID per individual for successful games was 9, while that for the unsuccessful games was 10.

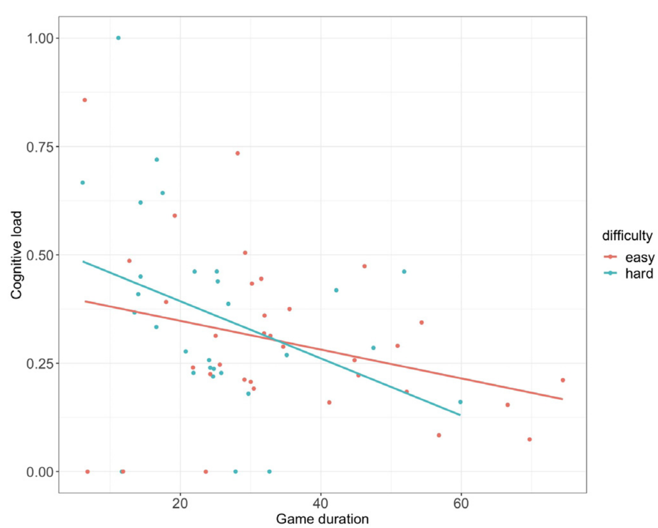

Fig. 7. Scatter plot between the cognitive load (x-axis) and game duration (y-axis) for the different game difficulty levels (color)..

5.3. Physiological fatigue, game duration, success, and difficulty

For R3, we analyzed the relation between physiological fatigue, game duration, game success, and game difficulty to investigate the correlations between participants' physiological fatigue and game success. We observed an interaction effect among the three variables (Fig. 8). There is a significantly negative correlation between the physiological fatigue and the game duration for successful games ($r(58) = -0.35$, $p = 0.03$) while there is no significant relation between the physiological fatigue and game duration for unsuccessful games ($r(30) = 0.18, p = 0.21$). Furthermore, there is no difference between the levels of physiological fatigue and the game difficulty (F[1,87] = 0.70, p = 0.40).

5.4. Cognitive load, gaze on ghost and success

Finally, typing R1 and R2 together, we investigated the relationship between cognitive load, gaze on ghost, and game success.

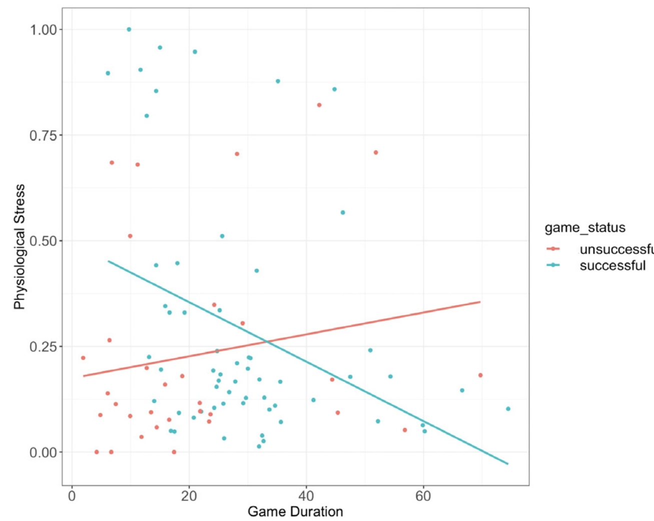

Fig. 8. Scatter plot between the physiological fatigue (y-axis) and game duration (x-axis) for the different game outcome levels (color)..

We found a significant interaction effect between the proportion of time spent looking at the ghost robot, cognitive load and game success. For the successful games there is a negative correlation between the cognitive load and the proportion of time spent looking at the ghost robot ($r(58) = -0.27$, $p = 0.04$). In contrast, there is no such correlation for the unsuccessful games ($r(30) = 0.01$, $p = 0.98$). Fig. 9 shows the relationship between the three variables. It is important to clarify that the points on the top-left and bottom-right of Fig. 8 are not outliers (they represent the minimum and maximum observed cognitive load, due to a MinMax normalization). The point on the bottom-right shows the maximum cognitive load (i.e., the highest cognitive load recorded, which does not depict "cognitive overload") and also it is possible to have all the attention on the ghost robot for a game (point on the top-left of Fig. 9).

6. Discussion and conclusion

In this paper, we investigated how the behavioral patterns, particularly those of attention, change for children with learning difficulties in a robotics-based game based on difficulty and success. Previous research has shown the impact of embodied learning on attention (Cassar & Jang, 2010; Frutos-Pascual et al., 2014), but there is less work on how to adapt these systems to users. A first step is to understand the current attention processes for which eye tracking can be used. For research question R1, we aimed to answer how the participants' processes changed between unsuccessful and successful games and easy and hard games. Particularly, we were interested in how the participants' attention to the robots fit into their game-play process and how the robot behaviors influenced these attention measures. For research questions R2 and R3, we aimed to answer how a participant's (R2) cognitive load and (R3) physiological fatigue changes throughout their session and in relation to game success and game difficulty. To address these questions, we used process mining to discover transition patterns between the relevant AOIs

in the game, and we analyzed the cognitive load and physiological stress of participants during the games in relation to game success and difficulty.

From our analysis, we found that the participants engaged in more direct transitions between the relevant AOIs in the successful games and had a different level of cognitive load. The process mining revealed that for unsuccessful games, the participants had

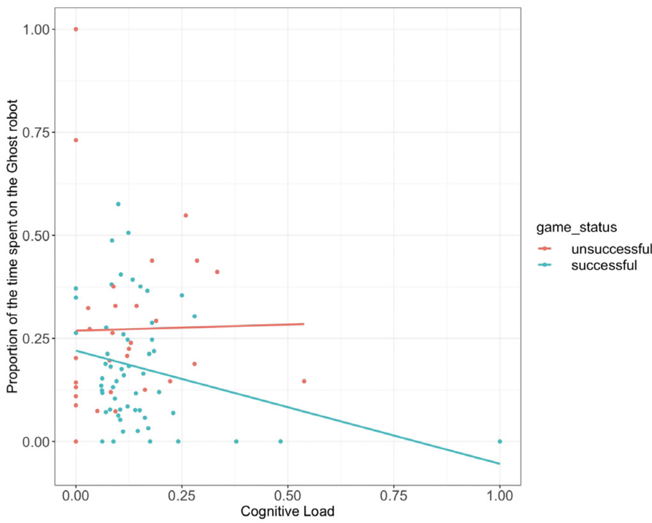

Fig. 9. Scatter plot between the cognitive load (x-axis) and the proportion of the gaze on the ghost robot (y-axis) for the different game outcome levels (color)..

other AOIs as a central event. In other words, the transitions between Target, Ghost, and Pacman fixations were interspersed with the participant focusing elsewhere in the game first. One exception is that the participants would look from the target back to their Pacman. In contrast, in successful games, the ghost robots were monitored more closely during the game play. In our model, this becomes apparent by the added transition from Target to Ghost and the lack of transition to Other. When a participant successfully completed a game, after focusing on a target, they would either focus on the ghost or Pacman. This difference with the unsuccessful games shows the importance of the attention to the ghost robots to not get eaten by them and lose the game. Additionally, this importance is reflected in the increased significance of the ghost node in the process model. These results are further supported in that there is no correlation between ghost fixations and cognitive load in an unsuccessful game but a negative correlation in a successful game. Paying more attention to the ghosts lowers the mental effort. Given these findings, we can support students when they have high mental effort by including interventions that help them to focus attention on the pertinent items at these times. For example, different ghost designs may be able to be used to draw the child's attention.

As with the game success, game difficulty impacted participants' processes. However, unlike game success, which is more closely tied to participants' individual performances, game difficulty is tied to the robot performance — specifically the speed at which the ghosts moved. For the easy games, we found a similar process to those of the unsuccessful games in which the Other AOI played a central role and a transition between Target to Pacman. For the hard games, we found a different process again bringing the ghosts into a more prominent role in the game play. In the hard games, there was no longer a transition between Ghost and Other. Rather, before focusing on a ghost, participants would often be focused on their own Pacman, and after focusing on the ghost, they would move focus towards the target. In this case, we have a loop between Target, Pacman, and Ghost. The more connected Ghost, Target and Pacman AOIs reflects the change in difficulty. As the ghost robots increase their speed, it is important to know where they are. It is not possible to keep moving towards the target if you will get blocked by the ghosts. At the higher speeds, this is more likely to happen and other strategies need to be put into place. This loop between the relevant AOIs may reflect that the student is more aware of all of the relevant parts of the game at any given time. As with the successful games, the increased significance of the ghost node in harder games also reflects the increased attention that it receives. These results demonstrate that game difficulty can mediate strategies and attention patterns, forcing individual to only focus on significant targets in harder games. This novel insight can be used in two ways: (1) as a diagnosis tool, to determine the difficulty for each individual by assessing if only significant AOIs are looked at and (2) as an adaptive tool to keep the child challenged by changing the game difficulty to keep the child in a significant AOI pattern.

For the cognitive load, we see that the games at the beginning of the session tend to have a higher cognitive load for both the successful and unsuccessful games. This result can be explained by participants learning to play the game. As they learn the rules and strategies, their cognitive load would decrease. In the later successful games, we again see an increase in the cognitive load. This is similar to other problem solving strategies where cognitive load was higher in the cases of high-performance (Van Gog, Kester, & Paas, 2011; Van Merrienboer, Schuurman, De Croock, & Paas, 2002). This change is most likely due to the later games being those of higher difficulty. When the participants are unsuccessful in a game, they do not pay as much attention to the ghosts, as we saw in our process models so the change in speed is unlikely to increase their load. In the successful games, the ghosts are a more integrated part of the participant's process and the increase in speed could explain the increase in the cognitive load. Our results highlight both the importance that a participant's attention can have on the outcome of an activity as well as how the actions of the robot can influence this attention. If a participant does not pay attention to the robot after critical moments in the process, for example, in this game being aware of the ghost location compared to the target, then the participant will not be successful in the task. The positive news is that we can design the robotic behaviors to influence the attention of the participant. As we saw with the change in game difficulty, a change in robot behavior can change the way that the participant integrates that robot into their process.

In this case, we may be able to use the adaptable robot behaviors to change the child's behavior. In easy games, there may not be enough engagement with the game to influence the children to beneficially regulate their attention behaviors. By extending the research that shows interest in a task is a mediating factor for self-regulation (Sansone & Smith, 2000), increasing a child's engagement with a task may support their attention regulation. By increasing the difficulty across games, hence making it more engaging, the children may begin to engage in beneficial attention patterns. However, as we saw from our results, the participants were not more likely to be unsuccessful during an easy than a hard game. This means at any given time, a child may disengage from the activity. From our results, we see that cognitive load may be able to be used as an indicator of this disengagement. If the child has a low cognitive load, it means they may be disengaged. We could adaptively adjust the ghosts' speed for a short period of time during the game to try to re-engage the child. Choosing the optimal game speed based on cognitive load is also supported within serious games (Petko, Schmid, & Cantieni, 2020). These two proposed adaptive behavior build upon our findings in this paper.

However, to assess if they have an impact on engagement and subsequently, skill acquisition, further studies are needed.

For future work, it is also important to consider the ethical issues that come with data collection from children. CCI researchers have always been cautious about ethical and privacy concerns (Dowthwaite et al., 2020; Kawas et al., 2020;

Van Mechelen, Baykal, Dindler, Eriksson, & Iversen, 2020). Preparations of studies using any sensing technology (including eye-tracking) require special attention and additional time to the ethics of data collection from a practical standpoint (Markopoulos, Read, & Giannakos, 2021). But the benefit with the eye-tracking is that the data can easily be kept anonymous because there is no video of the face or any audio files. In this way, eye tracking measure can provide a significant amount of data that can be used in as input into the system (Al-Shathri et al., 2013) without the children being watched or listened to. When it comes to the social aspects of the studies with children using the eyetracking, there are certain roles that the caregivers (in case of the children with special needs), parents, or teachers can play. These roles will not only allow the studies to be conducted in a smooth fashion but also might increase children's acceptance of the eye-trackers in a broader context than the one used in the study (Sharma & Giannakos, 2021). Finally, when it comes to children with special needs such as ASD and ADHD, an overwhelming proportion of such children often fail to achieve conventional independence as adults in terms of behavioral markers (Shattuck et al., 2012). The traditional intervention approaches might not be sufficient to create opportunities for addressing these skills and deficits within and across naturalistic settings in appropriately intensive sessions (Goodwin, 2008).

This work is not without its limitations. First, we have a small sample size of 17 participants. As these participants had a range of backgrounds, individual differences could sway our results. Second, in our study, the participants were given significant choice over their amount of interaction and difficulty level. It may be that the participants engage in different processes when they choose their difficulty rather than the choice being made for them, which is common in many adaptive systems. Additionally, in this paper, we focused on children with learning difficulties without a comparison to those without, and our analysis was limited to correlations due to this design. This limits us to control for factors in the study, which we would solve in the future by recruiting more children to have a critical sample to conduct repeated measure ANOVA. Such analysis will provide more robust results than the results based on the correlations.

Additionally, further research is needed to understand if similar patterns exist across groups. Finally, with a more controlled set of participants, further gaze analysis could be conducted to elicit the emergence of attention anchors used by participants when planning the path for Pacman to escape the ghost and reach the target (Abrahamson, Shayan, Bakker, & Van Der Schaaf, 2015).

In summary, analysis of eye-tracking data is a powerful tool to analyze processes and action patterns in robot–child games. While this work will be useful to our project in the design of adaptive game scenarios to train children with attention difficulties, we believe that the impact of it goes beyond this and could benefit embodied, game-based learning designs more broadly. We demonstrated how through using eye-tracking data, one can analyze the interaction as a whole and build a model of the user's cognitive processes. In particular, with our study, we found that:

- Specific gaze patterns and cognitive load are characterizing successful versus unsuccessful strategies.
- Increased game difficulty generates more focused game patterns on significant areas of the workspace.
- Cognitive load is correlated with attention to the meaningful elements of the game and could be used to put interventions in place.

This cognitive dimension is, we believe, crucial to take into account when building adaptive support systems.

Selection and participation

All the participants of the study were students from the Norwegian University of Science and Technology (CITY HERE, Switzerland). Studies took place at the school campus in the classrooms. Data related to the study were collected after approval from Ecole Polytechnique Federale de Lausanne, Switzerland, following all the regulations and recommendations for research with children. A researcher contacted the teacher and the legal guardian of each child to get a written consent that gave permission for the data collection. The children were informed about the data collection process and their participation in the study was completely voluntary. They could withdraw their consent for the data collection at any time without affecting their participation in the coding activity.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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