**Patricc, Child, Parent interaction**

**Roi Hezkiyahu**

[roihezkiyahu@mail.tau.ac.il](mailto:roihezkiyahu@mail.tau.ac.il)

Sagol School of Neuroscience ,Tel-Aviv University

Tel-Aviv, Israel

Under the supervision of:

**Omer Gvirsman,**

omergvir@mail.tau.ac.il

Curiosity Lab, Department of Industrial Engineering,

Tel-Aviv University

Tel Aviv, Israel

**Goren Gordon**

goren@gorengordon.com

Curiosity Lab, Department of Industrial Engineering

Sagol School of Neuroscience, Tel-Aviv University

Tel Aviv, Israel

**Abstract (1)**

There has been an increasing amount of research conducted to determine how a robot tutor influences language learning in children, most of this research was conducted on children aged 3-12, still the use case for robots for toddlers (ages 1-4) in their homes hasn’t gained similar attention. We investigate the influence of the Patricc robot, a specially designed robot for toddler-robot interaction, on the parent toddler interaction with comparison to a tablet interaction. We conducted a follow up study for the triadic interaction (with X parent-toddler pairs) in order to better understand patricc’s role in the social interaction and to better understand how we can utilize it. We used ganger causality in order to understand which interactions are linked be a cause-and-effect relation, also we compared the key features of the robot interaction versus the tablet interaction to understand how they differ. We saw that: results… This suggest that: Conclusion

**Introduction (1-2)**

Social robots are slowly taking place in our everyday activities, in our workplace [1], in agriculture [2], in medicine [3] and in educational systems [4] . the use of social robots has recently been explored in the educational system, with the expectation of positive feedback on learners [5]. Childhood education is an important issue and many researchers seek a way to improve current methods, especially Robotics researchers have been attempting to improve children education by introducing robots [9-11]. Most of the educational application are targeting children from preschool to adolescence, only a few studies have targeted toddlers from ages 1-4. These age group require a different approach as they require a triadic (Parent, Robot, Child) interaction as opposed to higher age groups which do not require help in handling the robot. They also require a different design for the robot because toddlers tend to physically interact with the robot and their attention span is much shorter, this is why a Platform for Triadic interaction (Patricc) has been represented [6]. Patricc is a 3D printed robot with changeable puppet-like characters, it lays on a platform which can be placed with physical educational props and can be easily integrated with new content via a specific made authoring tool for non-programmers.

There has been some research suggesting that a HRI (human-robot interaction) may increase the parent-child interaction and enjoyment of the experience [7], and also a robot touter might be better at teaching new words then humans [8]. Although it remains unclear whether their learning improved due to the presence of the robot or because children taught the words to another agent, the study demonstrated the unique role robots can play in vocabulary learning.

In this paper we present a comparison between the patricc interaction versus a tablet interaction, and investigate how does patricc interaction effect and contributes to the parent child interaction in English learning session for toddlers.

**Research question (0.5)**

We sought to investigate 3 main research questions:

Q1: How does the interaction with a robot differ from the interaction with a tablet?

We addressed this question by comparing different features of the interactions.

Q2: What patterns of the robot can contribute to the parent-child interaction?

We addressed this question by asking which features granger cause others

Q3: What are the main patterns for the parent-child interaction?

We also addressed this question with granger causality tests.

**Methods (2-3):**

**Data collection**

Audio and video data was collected for X pairs of parents and toddlers engaged in a hands-on activity with both the robot and tablet, during each activity the parent and toddlers participated in three learning sessions ordered RRT(robot, robot, tablet) or TRR (tablet, robot, robot). Each session had its own vocabulary set and was taught by a specific puppet.

Each session began with the puppet introducing itself followed by a song which included the vocabulary of the session, each time the robot sang about one of the vocabulary words he pointed and gazed towards the correct object. After the song the robot pointed and gazed towards each of the objects, this action was accompanied by saying the object’s name and asking the toddler to pick it up. After teaching all five objects the robot asked the toddler once again to pick up each object, this time without pointing and gazing at it. If the toddler picked up the correct object the robot gave positive feedback such as waving his hands and saying: “Very good”. If the wrong object was picked up then the robot told the toddler the name of the object that was picked up, asked the toddler to put it back and then repeat the name of the correct object to pick up. If the toddler did not pick up anything the robot would encourage the toddler by saying “Try again, you can do it!”. Only after the correct object was picked up the robot continued to the next word. After finishing all the words the robot waved his hand and said “Goodbye, see you soon”.

**Data annotation:**

To analyze the videos we used the thin slice approach [12] with a 15-second slices. The interactions were manually coded by X coders. Each coder coded Y% of the videos. Inter-rater reliability (Cohen’s kappa) was assessed on a set of Z randomly selected videos (% of the data). The average kappa score Z with the lowest Z , indicating ? reliability for all codes [13]. the behaviours that were coded are:

|  |  |  |
| --- | --- | --- |
| Action | Sub actions | Who |
| Gaze | At: Parent/Toddler, props, robot, tablet | Parent, Toddler |
| Gesture | point at prop | Parent, Toddler |
| prop manipulation | - | Parent, Toddler |
| utterance |  | Parent, Toddler |
| affective touch |  | Parent |
| affect | positive1, positive2, positive3 | Parent |
| pointing |  | robot |
| robot text | pick up, positive feedback, put down, song, teach, try again | robot |
| Verbal scaffolding | affective, cognitive, technical | Parent |
| Conversational turns\* | PT (Parent, Toddler), TP, TPT, PTP | - |
| Joint attention\* | At props, robot, tablet, mutual gaze | Parent, Toddler |

Table 1: Specification of the coded features

\*features that were created from the annotated data

**Data processing:**

We pre-processed the data before the analysis, first we cut the video to contain only the interaction, afterwards we created the conversational turns and joint attention features from the annotated data. Conversational turns were counted as PT if the parent talked and the toddler started talking 1 second after the parent started talking and 5 seconds after he had finished talking, TP was counted the same, PTP and TPT where counted the same way. The conversational turns were timed from the second that the first talker started until talking the time the second (or third) talker ended talking. Joint attention were counted if both parent and toddler gazed at the same thing (or at each other), it was timed from the moment they both gazed together until one of them has finished gazing. The data was then transformed into a time series, the rows were time stamps from the video with a window width of 0.5 seconds, the columns are the annotated features. Each cell in the matrix was given the value 1 if the event of the column occurred at the time window, otherwise it was 0.

**Analysis:**

To better understand cause and effect relations between 2 distinct features we build a GUI to present a time window histogram. Our time window histogram was created by fixating one feature and counting how many events occurred several seconds before and several seconds after that said feature occurred. For example: if a child pointed at the props in second 10 we counted the number of times the parent gazed at the props in seconds 7-,8,8-9,9-10,10-11,11-12,12-13,13-14,14-15. We counted the number of events for each second that the child pointed at the prop and made a histogram. This GUI helped us to better understand the changes within the interaction.

Chart, treemap chart

Description automatically generated

Figure 1: GUI example

Counted events histogram for events accruing before and after child pointed at prop at one of the trails

**Comparison of interactions:**

**Granger causality :**

**Results (with graphs, statistics, legend, and description)**

**Discussion(3-4 including the results)**

References and notes

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