Growing Growth Mindset with a Social Robot Peer

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ABSTRACT

Mindset has been shown to have a large impact on people's academic, social, and work achievements. A *growth mindset*, i.e., the belief that success comes from effort and perseverance, is a better indicator of higher achievements as compared to a *fixed mindset*, i.e., the belief that things are set and cannot be changed. Interventions aimed at promoting a growth mindset in children range from teaching about the brain's ability to learn and change, to playing computer games that grant brain points for effort rather than success. This work explores a novel paradigm to foster a growth mindset in young children where they play a puzzle solving game with a peer-like social robot. The social robot is fully autonomous and programmed with behaviors suggestive of it having either a growth mindset or a neutral mindset as it plays puzzle games with the child. We measure the mindset of children before and after interacting with the peer-like robot, in addition to measuring their problem solving behavior when faced with a challenging puzzle. We found that children who played with a growth mindset robot 1) self-reported having a stronger growth mindset and 2) tried harder during a challenging task, as compared to children who played with the neutral mindset robot. These results suggest that interacting with peer-like social robot with a growth mindset can promote the same mindset in children.

Keywords

early childhood education, mindset, perseverance, grit, child-robot interaction, cognitive architecture, social robots

1. INTRODUCTION

Psychologists have shown that beliefs about the malleability of human attributes such as intelligence can have strong effects on motivation, reaction to challenge or failure, and academic achievement [4, 12, 17]. Mindset, according to Dweck [8, 33], dictates how people perceive their own and other people's capabilities, behaviors and attitudes. People with a *fixed mindset* think that nothing can be changed – that capabilities are fixed and cannot be improved. People with a *growth mindset* believe that achievements are dictated by effort and resilience to failure, often referred to as grit [7]. It has been shown that people with a growth mindset have higher academic, social, and work achievements [4, 30, 33].

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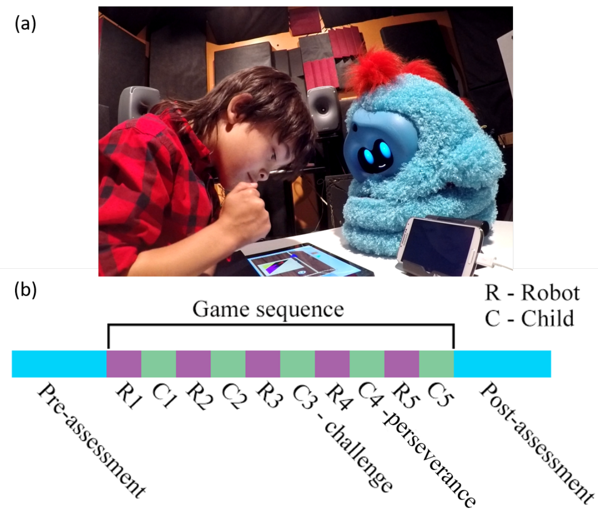

Figure 1: (a) Experimental setup including Tega, tablet and child; (b) sequence of the experiment and sequence of the puzzle solving turns between the robot and the child over 5 rounds.

1.1 Background & Related Work

Several intervention strategies have been developed to promote a growth mindset, especially in children [22, 4, 3, 12, 19]. In [24], an educational online game was developed and demonstrated to encourage the growth mindset by incentivizing effort, use of strategy, and incremental progress through a "brain points" score system.

Both laboratory and classroom studies have shown that mindset can be changed through careful intervention, often involving social interaction [8, 16, 4, 22, 19]. For instance, directly teaching students that intelligence is malleable has been shown to improve classroom motivation and achievement compared to a control group [4]. Praising children for their strategy or effort as they solve problems (rather than praising their talent) produces a growth mindset, higher motivation, and task persistence [22, 19]. These interventions not only change people's attitudes, they also positively impact achievements [9]. Unfortunately, praising children in a way that reinforces a fixed mindset can have negative consequences. Gunderson et al. [16] have confirmed the role of praise in mindset, showing that the type of praise parents give to young children predicts the child's mindset five years later.

These kinds of adult-child interventions are important. However, peer-to-peer interactions can also have an important influence on children's attitudes and behaviors. The impact of peer influence on children's mindset, however, has yet to be studied in a methodological way.

Social robots as educational companions for children have been recently explored in a growing breadth of scenarios including vocabulary acquisition [21, 31], second-language learning, mathematics, computational thinking, and social skills [27, 26]. The interaction skills of such robots have been found to impact children's behavior and learning in important ways. It has been shown that children treat robots as informants [6] and positively respond to personalization of affective, verbal and nonverbal behaviors [15].

Especially noteworthy is that social robots can promote higher level motivational attributes and cognitive skills. For example, Alves-Oliveira et al. [2] explores the use of social robots to promote creativity in children. Social robots portrayed as curious, peer-like learning companions have been shown to promote curiosity in children via co-play [14, 13].

1.2 Overview

In this paper, we investigate whether social robots, framed as peers, can promote a growth mindset in children. To address this question, we first developed an expressive cognitive architecture that combines problem solving with mindset driven expressiveness. We use this architecture to generate the behaviors of a child friendly social robot that are indicative of having either a neutral or growth mindset. We then designed and conducted a novel study in which children played spatial puzzle solving games with either a growth or neutral mindset robot. The robot was introduced to each child as a playmate and had a similar puzzle-solving skill level as the child.

We developed a suite of novel apps for this purpose including a Tangram game app and two pre/post assessment activity apps to measure mindset and spatial skill [5, 28]. The child and robot take turns selecting which puzzles to try and solve under time pressure. In the growth mindset condition (GROWTH), the robot selects the more challenging tangrams to solve and makes growth mindset related comments about its own and the child's abilities and efforts throughout the session. In contrast, in control condition (NEUTRAL), the robot selects similar difficulty level tangrams as the child and makes neutral comments, mainly factual statements about the success or failure of the task. Towards the end of the session, a particularly challenging, time limited tangram puzzle is used to confront children with failure. After this, another challenging tangram, but with no time limit, was used to assess children's perseverance. Children's answers and behaviors during these activities were measured and analyzed to determine how each condition influenced children's mindset as expressed through their beliefs and actions.

1.3 Contributions

This paper presents a first of its kind growth mindset intervention study using an autonomous robotic agent. Specifically, we offer the following contributions. We developed novel assessment apps for measuring children's spatial reasoning skills and mindset. These shall be made open source[1]. Second, we designed and conducted a novel study to explore the effect of peer-like interaction on children's mindset. It is also the first study to investigate the effect of a peer-like social robot on chidren's mindset. Finally, our results support our main hypothesis, namely, that interacting with a peer-like robot that expresses a growth mindset has a positive impact on children's mindset as expressed through their communicated beliefs and task-based behaviors in the face of challenge.

2. SYSTEM DESCRIPTION

The system is composed of *Tega* as a social robot platform, an *expressive cognitive architecture* that supports problem solving as well as generating mindset driven robot behaviors, and a *tablet* as a shared space for presenting child-robot interaction tasks such as the *Tangram puzzle app* (Figure 1(a)). Data exchange takes place over the network in which each module publishes its states and actions and subscribes to others' messages. The Robot Operating System (ROS) [29] handles the synchronization of these messages.

2.1 Robot Platform

Tega is an appealing, expressive, child friendly robot, designed for long-term deployment in various educational settings such as children's homes, schools, and therapeutic centers [32, 15]. It is a size of a teddy bear (about 11 inches tall) and is brightly colored with a plush exterior. It has five degrees of freedom to perform a wide range of expressive movements: head tilt up/down, waist tilt left/right, waist lean forward/back, body extension up/down, and body twist left/right. The robot has an efficient battery-powered system that can run for up to six hours before needing to be recharged. An Android smartphone mounted in the head is used to graphically display the robot's animated face as well as perform computational tasks such as sensor processing, data collection, wifi communications, decision making, and motor control. The robot's electronic design extends the smartphone's ability with on-board speakers and an additional high-definition camera with a wide field of view.

Tega is a peer-like social robot. A *peer* is a group of people in similar ages that influences each other's language, behavior, and beliefs through interaction. Tega's peer attributes include child-like high pitched voice, exaggerated body and facial expressions, as well as its intrinsic tangram solver that mimics the thought process of a child in terms of spatial reasoning and speed. With its peer attributes, Tega is able to engage in taking turns solving a puzzle with a child while encouraging each other. Combined with the expressive cognitive architecture presented in the following section, Tega can reason about the child's cognitive states and express its

[1]The assessment apps will be made available with documentation in June 2017 in the following link: https://github.com/CuriosityLabTAU

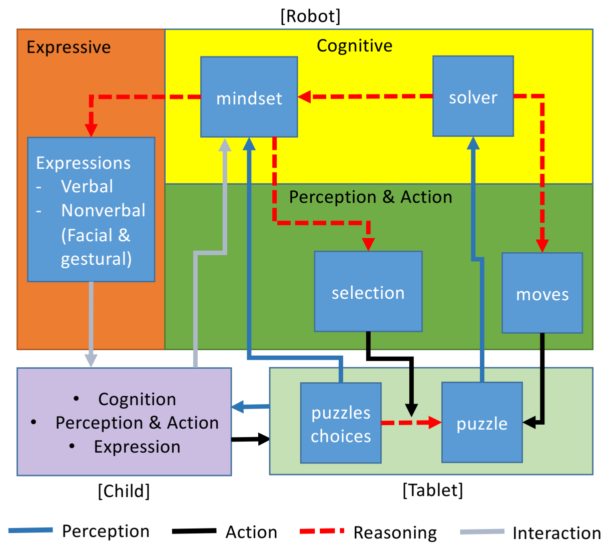

Figure 2: The expressive cognitive architecture that combines problem solving with mindset driven expressiveness. The modules within the robot are computational mental models mimicking those of the child's.

(a) Tangram selection: "I will choose this one because it looks challenging"

(b) Child win: "You worked hard and succeeded! Yay!"

(c) Perseverance task: "you are working hard to solve this puzzle"

(d) Game end: "We worked hard and succeeded!"

Figure 3: Utilizing its expressive cognitive architecture, Tega expresses its mindset in various stages of the interaction through verbal and nonverbal behavior.

growth mindset mental model through a set of verbal and nonverbal behaviors.

2.2 Expressive Cognitive Architecture

The expressive cognitive architecture bridges an algorithm for solving tangram puzzles to generating robot's mindset dependent expressive behaviors. The idea is that, within a context of tangram puzzle solving, we are creating a computational mental model of a child's cognitive processes (mindset and puzzle solver), perception and action (puzzle selection and making moves), and expressiveness (verbal and nonverbal behavior based on the mindset state). This mental model is then applied to Tega for it to generate tangram solving and mindset oriented expressive behaviors. With such a model, a robot can not only act more peer-like, but can also help foster a growth oriented mindset in children by setting an example. For instance, by selecting a more challenging puzzle and demonstrating that one can also learn by failing, a child may overcome her fear of making mistakes. As depicted in Figure 2, the mindset module is triggered by the information flow from the surrounding modules and the environment: the child, tablet, and the solver. Using this information, the mindset module creates an assumption of the task and the child's states. It also generates its next set of actions, such as commanding the expression-generation module to produce robot behavior or making a puzzle selection based on its mindset. The modules exist within the robot enabling it as an autonomous agent. Hence, in the tablet's perspective, the child and the robot are just individual players.

During its turn, the robot solves a tangram puzzle and performs actions on the tablet game using a neural network solver. The tangram solving algorithm is a neural network model following Oflazer's connectionist approach [23]. Each tangram piece, represented combinatorially by its position and rotation on a puzzle grid, is mapped to a node in the network. Their inhibitory connectivity represents physical constraints, such as uniqueness of pieces and their non-overlap in possible solutions. The nodes are then excited by their relative overlap with the input tangram silhouette, akin to how humans mentally align tangram pieces to the silhouette when first confronted with a puzzle. A relaxation search algorithm is performed according to the Bolzman machine model [1], converging to the puzzle solution. The active nodes for each search iteration are then serialized to produce a sequence of moves toward a solution. This serialization step is analogous to the thought process of a person when confronted with a new puzzle.

The expression-generation module takes the state of the task as an input to generate the robot's nonverbal and verbal behaviors. Throughout the session, this module generates expressive behaviors, coordinating the robot's physical movements, facial expressions, and vocalizations so that the robot can produce behavior during its own and the child's play. In the growth mindset configuration, the robot detects the state of a child's effort and provides comments and encouragements on the child's perseverance and willingness to take on challenges, as depicted in Figure 3. In the neutral mindset configuration, the robot simply acknowledges and provides factual comments on the success or failure of itself and the child's. Details on robot's speech examples are presented in Section 3.4.

2.3 Tablet Shared Workspace

Recently tablets have been extensively used as a shared human-robot interaction space, due to it's inviting interface both for the person (touchscreen) and the robot (wireless communication) [25]. The tablet is an Android device with a 10-inch screen. The following three apps were installed on the tablet: the main Tangram app and two apps corresponding to digitized assessment activities to measure mind-

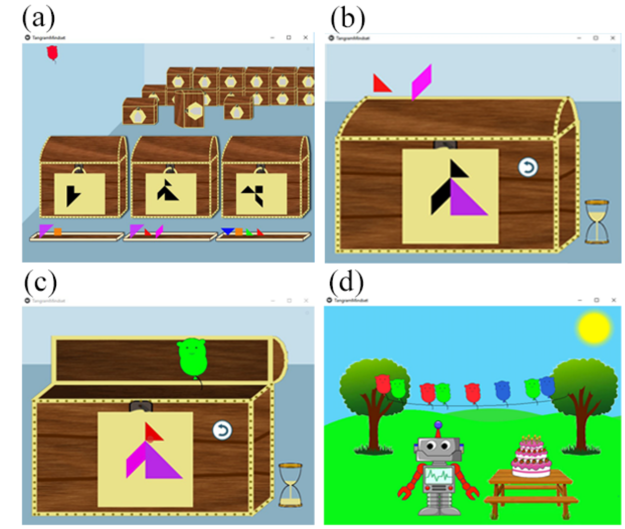

Figure 4: Screenshots from the Tangram App: (a) tangram selection room, (b) solving a tangram puzzle, (c) puzzle solved, (d) party screen.

set and spatial skill. The tablet also performs data collection, recording how children and robot play with these apps. For instance, in the tangram app, the states of the tangram game, touch events, hourglass events, tangram piece locations, number of attempts and timestamps, player turns, and puzzle selections are logged.

2.4 Tangram Treasure App

The tangram app is designed as a game where the objective is to collect balloons to decorate a birthday party. To get a balloon, the player needs to unlock treasure boxes, each holding a balloon inside. To unlock a treasure box, the player needs to solve a tangram puzzle depicted as a silhouette on the outside of the box.

Each round, three tangram puzzles are generated to produce three distinct levels of difficulty. The difficulty level of a puzzle is determined by the number of pieces and the total length of joint piece edges. At the beginning of each turn, the player first selects one out of three treasure boxes, ordered by difficulty, with the left being the easiest and the right the most difficult (Figure 4(a)). Upon selecting a treasure box, the player needs to unlock it by solving the tangram puzzle in less than 2 minutes (Figure 4(b)). Otherwise, the treasure box remains locked with the balloon inside. If the player solves the tangram puzzle, the treasure box is unlocked and one balloon is gained (Figure 4(c)).

If the player succeeds at solving any of the puzzles, the difficulty level of the next round increases by one. If the player fails, the difficulty level remains the same, unless this happens on the easiest puzzle. In this case, the difficulty level for the next round decreases by one. By proceeding in this way, the goal is to challenge the child while maintaining a level matched to her performance.

The game ends with the party scene with all the acquired balloons decorating the scene (Figure 4(d)).

2.5 Mindset Assessment App

Our mindset assessment app probes children's beliefs about their own mindset through introducing two characters and asking the child which character they agree with more over a series of statements they make. The statements used in the app are based on Dweck's mindset questionnaires [8], and the age adjusted statements are adopted from [18]. Two characters appear on the screen, Buffy and Fluffy, accompanied by the following instructions by the app: "This is Buffy, and this is Fluffy. They are siblings. Buffy and Fluffy really like school, and they want to know if you like school, too! Buffy and Fluffy want to know more about what you like or don't like about school. They will tell you about how they feel, and then I want you to pick whether you are more like Buffy, or more like Fluffy. Okay? Are you ready to play?" (Figure 5(a)).

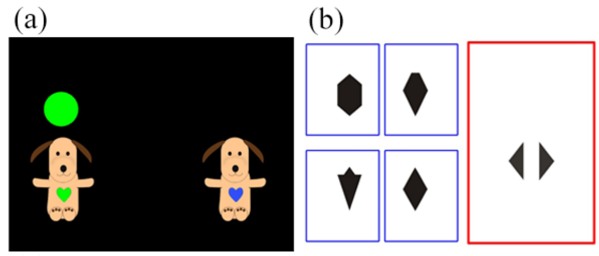

Figure 5: Screenshots from: (a) mindset assessment app, (b) spatial skill assessment app.

Buffy and Fluffy each take turns saying one statement with a green/blue circle over the head of the character who is talking. In total, ten pairs of statements are presented to the child, one sentence representing a fixed mindset and the other representing a growth mindset. For example, in a given selection task, either Buffy or Fluffy makes a fixed mindset statement "I like school because I'm really good at the things we do there", and the other makes a growth mindset statement "I like school because I learn to be better at things we do there". Then the child is prompted to answer "which one is more like you?" by clicking on either Buffy or Fluffy.

The variables that may cause bias in the study results are carefully controlled. We use gender neutral names and colors for the two identically looking characters and vary which character delivers the growth mindset statement in each turn. To control for ordering effects, the ten statements are presented in randomized order. Participants play this app as a pre/post assessment. Five of the ten statement pairs are identical in the pre/post assessments, and five are different. The app records the selections the child makes and the associated time. None of the statements used in the mindset assessment are used by the robot during the tangram interaction.

2.6 Spatial Skill Assessment App

Our spatial skill app is based on the Children's Mental Transformation Task (CMTT). The task is designed to test four types of 2-D mental transformations: 1) horizontal translation, 2) diagonal translation, 3) horizontal rotation, and 4) diagonal rotation [20, 10].

In this task, participants choose which shape would be made by moving two separate pieces together. The app instructs the children to "Look at these two pieces on the red card. Now, look at these pictures on the blue cards. If you put the two pieces on the red card together, they will make one of the pictures on the blue cards. Press the picture on the blue card made by the two pieces on the red card." (Figure 5(b)).

The spatial skill app is used as a pre/post assessment. Each time the app is played, it presents 16 items in randomized order. A different set of 16 tasks is used between the pre/post assessments. The app measures the number of correct answers (0-16) and the selection time per item.

3. EXPERIMENT DESIGN

We designed a novel experiment to investigate a set of hypotheses regarding the impact of interacting with a peer-like robot with a growth mindset on children's own expression of mindset as measured via our assessment apps.

3.1 Hypotheses

The main hypothesis is that interacting with a robot that expresses a growth mindset will have a positive impact on fostering children's growth mindset. More formally, we hypothesize two condition dependent effects:

- **H1**: Participants in the growth mindset condition (GROWTH) will score higher on the post mindset assessment app compared to the control condition, i.e., neutral mindset condition (NEUTRAL).
- **H2**: Participants performing the perseverance tangram task (i.e., the challenging puzzle with no time limit) will have condition dependent behavior, i.e., not quitting and trying harder in the GROWTH condition, compared to the NEUTRAL condition.

With respect to learning gains from this short, single-shot encounter, we anticipate seeing a small pre-to-post increase in spatial skills as measured by the child's performance on the spatial skill assessment app. However, we do not expect to see a condition dependent effect, since the impact of having a growth mindset associated on learning gains is typically a longitudinal effect.

- **H3**: A small condition independent improvement in children's spatial skills will be observed.
- **H4**: Children perceive that the GROWTH condition robot has a growth mindset.

3.2 Participants

Participants were recruited from a mailing list of local families with young children. Forty children between the ages of 5–9 years old (age $M = 6.75$,$SD = 1.08$; female 42.5%) participated in the study. Participants were randomly assigned and counter-balanced across conditions with respect to their age and gender: NEUTRAL condition ($N = 20$, age $M = 6.75$, $SD = 1.07$; female 45%); GROWTH condition ($N = 20$, age $M = 6.75$, $SD = 1.12$; female 40%).

3.3 Conditions

The robot's behavior differed – reacting to the child's actions and to the state of the game with different verbal phrases, facial expressions and body movements – according to either the the experimental (GROWTH) condition or the control (NEUTRAL) condition. The robot chooses its reactions from a large collection of phrases and expressions that were carefully predefined to be appropriate for each condition. For example, when the child succeeds in solving a tangram puzzle in the NEUTRAL condition, the neutral robot makes a calm, factual statement "You solved the puzzle" with a head nod. In contrast, the growth mindset robot makes an affirming statement in the GROWTH condition: "You are not afraid of a challenge. I like that!" with accompanying body language and facial expressions showing excitement.

How the robot chooses tangram puzzles to solve also differs across conditions. In the NEUTRAL condition, the robot chooses a puzzle of the same difficulty level as the child, or easier. Recall that the puzzles are spatially ordered in levels of difficulty. Hence, if the child selects a tangram puzzle in a certain position and succeeds in solving it, then the robot selects the puzzle in the same position on its turn. If the child fails on her turn, the robot chooses a puzzle one level easier (if possible). In contrast, in the GROWTH condition, the robot selects a puzzle one level of difficulty higher (if possible) when the child succeeds in solving her puzzle, or chooses one at the same level of difficulty if the child fails. In this away, the GROWTH condition robot favors more challenging puzzles relative to the child's selections.

3.4 Protocol

The experimental protocol followed three stages: 1) Welcome and pre-assessment activities, 2) Playing the tangram game with Tega, 3) post-assessment activities.

3.4.1 Playing Pre-assessment Games

At the beginning of each session, the experimenter invites the child to play several games on a tablet before playing with the robot, Tega. At the same time, the parent is asked to fill out a questionnaire. We inform the participants that they can stop at any moment, if they are bored or do not wish to continue for whatever reason. If the child agrees to play, the first game is the spatial skill app with 16 tasks requiring children to choose which shape results from moving two separate pieces together. Next, the child plays the mindset assessment app comprised of 10 pairs of statements from Buffy and Fluffy, where the child chooses which one is more like him/her.

3.4.2 Playing Tangram Puzzles with the Peer-like Robot

After playing the pre-assessment apps, the child is brought to another area where the Tega robot sits on a table with a tablet nearby. The child is invited to sit on a chair facing the robot, with the tablet between the two of them. The child is told that Tega is a "young robot who wants to play a game with you." Tega's verbal and nonverbal expressions throughout the interaction were condition dependent (see Table 1), where each of sentence was randomly selected from a pool of 6 slightly different sentences. All of Tega's sentences were followed by a gesture that expressed an appropriate nonverbal expression, e.g. engagement, interest, excitement, frustration.

When the child first sees Tega it is "asleep" with its eyes closed, making sleeping sounds. The experimenter starts the interaction by waking the robot up. Tega yawns and introduces itself "Hi, I am Tega. My friend is having a birthday party. Everything is set but the balloons. Will you help me find some balloons?". On the tablet, the child sees a robot standing in a birthday party scene but with no balloons.

Table 1: Examples of robot behavior across conditions and interaction stages

Stage	NEUTRAL	GROWTH
Tega tangram selection	"I will choose this one."	"I will choose this one because it looks challenging!"
Child tangram selection	"start by selecting a box", "which box do you want to select?"	"try hard and you will succeed", "I'm sure you can do it if you try hard"
Tega tangram solution	"there", "I will move this piece.", "it's hard."	"it's quite hard, so I will try even more.", "if I keep trying, I will succeed.", "I'll try again."
Tega win	"great, I got us another balloon for the party", "I solved the puzzle'	"that was hard, but I tried hard and nailed it", "working hard is worth it"
Child win	"good job.", "great playing.", "You seem to be on the right track."	"you worked hard and succeeded!", "Working hard is worth it.", "you are not afraid of a challenge. I like it!"
Tega lose	"that was hard", "I did not succeed", "that was difficult"	"next time I will put more effort", "I'm not afraid of a challenge. I like it!"
Child lose	"next time, friend", "better luck next time"	"you worked hard, next time you will succeed", "you tried very hard. That's what matters", "you are not afraid of a challenge"
Game end	"we had a great game together"	"we worked hard and succeeded"

To start playing the tangram game, the child clicks on the "yes" button on the screen when Tega finishes delivering its line (alternatively, the child can click the "no" option). If the child does not respond to the initial prompt, the robot will invite the child to play two more times. Otherwise the session stops.

If the child clicks the "yes" button, Tega responds with "Great, let's play. We need to go to the magic treasure room" (followed by excited expression). The tablet changes the scene to the magic treasure room, and Tega explains the task "This is the magic treasure room. It is filled with magical treasure boxes. In each treasure box you will find exactly what you seek if you can open it. The lock to each magic box is a puzzle. First we need to choose which box to try and open" (Figure 4(a)). Tega begins by playing the first round of the game, demonstrating how to select a box.

Next the tablet screen changes to the selected box (Figure 4(b)). Tega explains: "These puzzles are made of pieces of different shapes. We need to find where to put them to fill in the gray area. We have two minutes to try, until the sand in the hourglass runs out." (then the robot leans forward to look at the game). The robot tries to solve the puzzle as aforementioned in the expressive cognitive architecture section. Tega comments as it tries different moves based on the experimental condition. The first round ended with Tega successfully solving the first puzzle and earning a balloon (Figure 4(c)).

After Tega solved the first puzzle the screen changed back to the magic treasure selection room and Tega told the child: "It is your turn now" followed by a condition dependent utterance. The child and robot take turns, choosing and solving puzzles to earn balloons to decorate the party scene. Overall, they play 5 rounds of the game starting with Tega the Robot (R1) followed by the Child (C1), until the game ended with the child last turn (C5) (Figure 1(b)).

The difficulty level of the tangram puzzles changes according to the child's performance in the previous round, with the following two important exceptions. Round 3 is the **timed-challenge round**, where the game presents three difficult puzzles having more pieces. These tangrams were designed to be difficult for children to solve, allowing us to observe their behavior in the face of failure, and also enabling Tega to respond to the child's failure. Round 4 is the **perseverance round** where three challenging tangram puzzles are presented, but with no time constraint for solving. During the perseverance round it is possible to observe the level of perseverance of the child during a difficult task, whether the child keeps on trying harder or gives up over time. The final round included three doable tangram tasks, with the goal of finishing the experiment on a positive note. If at any point during this game the child appeared particularly frustrated, the experimenter reminded the child that it was OK to stop at any time.

After solving the puzzles, the game concludes at the birthday party location, where all the earned balloons decorate scene. Tega concludes the game and says goodbye based on the condition, followed by falling asleep.

3.4.3 Post-interaction assessments

After playing with the robot, the experimenter asks the child to play the three assessment apps to post-test any changes to the child's spatial skills and mindset. As discussed, both are varied from the pre-test versions. In addition, the participants were asked to answer a short questionnaire regarding their perception of Tega's mindset. In total, 10 questions were asked, among which 5 questions were growth mindset oriented and others fixed mindset oriented statements. Five-point Likert scale measured the level of participant's agreement to a given statement (always no, sometimes no, maybe, sometimes yes, always yes). The overall score was summed by assigning 0–4 points to each lowest level to highest level agreement in the growth mindset statements, and 4–0 points in the fixed mindset statements (hence the maximum one can score is 50, minimum 0).

4. RESULTS

In the following analyses, we ran Shapiro-Wilk (S-W) test to check for normality and Levene's test to check for equal variance, where applicable. We failed to reject Levene's null hypothesis at the 0.05 significance level for all dataset ($p > 0.05$), hence we conclude that there is insufficient evidence to claim that the variances are not equal. Hence, parametric (paired/unpaired t-test) and non-parametric (Wilcoxon signed-rank and Mann-Whitney's U) tests were used based on the S-W result.

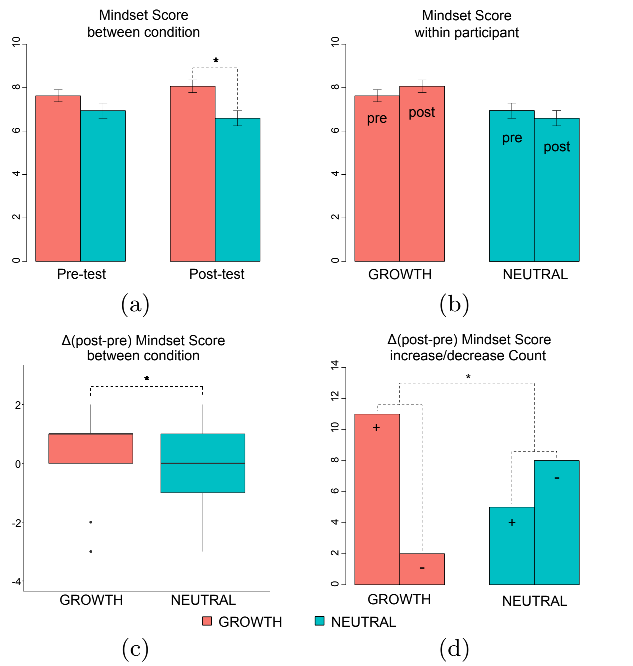

Figure 6: Analysis on children's mindset before and after interacting with the robot. Children who engaged with a growth mindset oriented robot showed an increase in self-reported growth mindset, a significant difference to the NEUTRAL group.

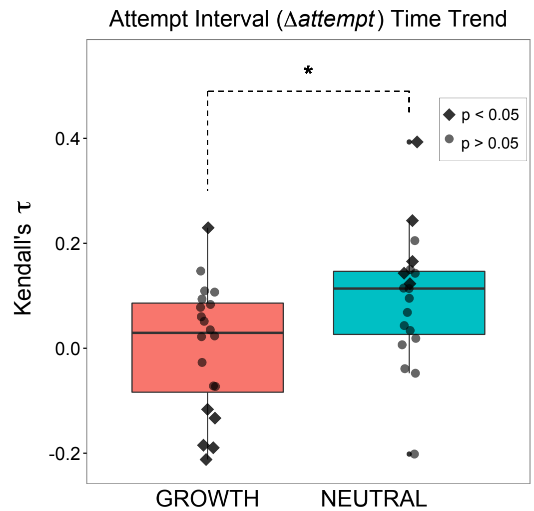

Figure 7: Time trend analysis on attempt intervals ($\Delta attempt$) was conducted in the perseverance round (C4). Result shows that children who were interacting with a growth mindset oriented robot significantly demonstrated more perseverance when confronted with a challenge. Diamond markers show trends with significance.

4.1 Mindset Assessment

In total, 33 children out of 40 completed the pre/post mindset tests. One child refused to participate in the pre-test, and six children either had to leave or refused to complete the post-test. Out of 33 children, 17 were in the NEUTRAL condition (age M = 6.88, SD = 1.05, female 41%), and 16 in the GROWTH condition (age M = 6.69, SD = 1.14, female 38%).

We summed the number of growth mindset oriented statements each participant chose among the 10 pairs of statements in the pre- and post-tests. Participants started out having a similar mindset score regardless of condition, with no significant statistical difference between conditions (NEUTRAL: M = 6.94, SD = 1.78, GROWTH: M = 7.63, SD = 1.41; t(31)= -1.22, p=0.23). However, more participants in the GROWTH condition scored higher in the post-test. We found a significant effect per condition (NEUTRAL: M = 6.59, SD = 1.77, GROWTH: M = 8.06, SD = 1.48; t(31)= -2.59, p=0.01) (Figure 6(a)). Fischer's exact test also revealed that the number of participants whose mindset score increased versus decreased significantly differed by condition (p = 0.041, odds ratio is 7.99) (Figure 6(d)). Mann-Whitney's U test showed that the amount of change pre-to-post was also significant with participants in the GROWTH condition, showing a stronger trend towards an increased growth mindset as compared to the NEUTRAL condition (Figure 6(c)). The mean ranks of the NEUTRAL and GROWTH conditions were 13.88 and 20.31, respectively; W = 83, Z = -2.00, p = 0.045, r = 0.35.

Taken together, these results suggest that there was no significant difference in mindset before the interaction with the robot. However, children's growth mindset increased after the interaction with a peer-like robot with a growth mindset. This confirms our main hypothesis **H1**.

4.2 Perseverance Assessment

All 40 children participated in the Tangram activity with the robot. The data of one participant was corrupted due to a network problem. Among 39 children, 19 were in the NEUTRAL condition (age M = 6.68, SD = 1.06; female 47%) and 20 were in the GROWTH condition (age M = 6.75, SD = 1.12; female 40%).

We analyzed children's perseverance during round 4 (C4) by presenting a difficult puzzle with unlimited time for solving. Perseverance is a steady persistence in a course of action in spite of difficulties. As a measure of perseverance, we evaluated the trend of puzzle solving attempts a child makes over time. The app recorded the timestamps of when a puzzle piece was manipulated by the child. The time difference between two consecutive events ($\Delta attempt$) was computed to analyze the trend of attempts. If a child consistently makes more attempts over time, indicated as a decrease in $\Delta attempt$, it is regarded that the child has perseverance. On the other hand, a child who consistently attempts less over time, indicated as an increase in $\Delta attempt$, was considered as showing less perseverance. Using Mann-Kendall trend test, we analyzed each participant's significance in the $\Delta attempt$ trend (derivative of $\Delta attempt$). Kendall's correlation coefficient τ ranges from -1 (100% negative association, or perfect inversion) to +1 (100% positive association, or perfect agreement).

We used an unpaired t-test on Kendall's coefficients between conditions. The result revealed a significant effect between conditions (NEUTRAL M = 0.0933, SD = 0.13, GROWTH M = 0.0016, SD = 0.12; t(37) = 2.3053, p =

0.02686, Cohen's d=0.74), the GROWTH condition showing a stronger trend towards more perseverance. In Figure 7, the *tau* coefficient values for all participants are shown. The diamond markers indicate individuals with a significant trend in $\Delta attempt$. A Freeman-Halton extension of the Fisher exact probability test on the trend result summed into three categories ("significant positive", "significant negative", and "no significant change") also revealed a significant effect between conditions (p=0.022) in the trend direction. Namely, the GROWTH condition showed strong negative trend (demonstrating increasing perseverance over time) while the NEUTRAL condition showed positive trend.

In summary, children's perseverance behavior was measured by the change in the frequency of their attempts over time. Children in the GROWTH condition showed a stronger trend towards an increased frequency of attempts over time compared to the NEUTRAL condition, supporting our second hypothesis, **H2**. While most participants showed a steady frequency of attempts from beginning to end when solving a difficult puzzle, more participants who interacted with the growth mindset robot strongly demonstrated more resilience to failure over time.

4.3 Spatial Skill Assessment

In total, 36 children completed the pre- and post- spatial skill assessment app. One refused to participate in the pre-test, and three children either had to leave or refused to complete the post-test. Out of 36 children, 20 were in the NEUTRAL condition (age $M = 6.75$, $SD = 1.07$, female 45%), and 16 in the GROWTH condition (age $M = 6.69$, $SD = 1.14$, female 38%).

We summed the number of CMTT puzzles each participant answered correctly in pre- and post-tests. The medians of the pre- and post-tests were 12 and 13, respectively, showing a slight increase. Using the Wilcoxon signed-rank test, we found a significant effect on children's score before and after playing tangrams with the robot. The mean ranks of the pre- and post-tests were 31.26 and 41.74, respectively; W = 52, Z = 7.38, p < 2.2e-16, r = 1.23. All other between condition pre- and post-analyses, including Mann-Whitney's U test and Chi-square test, revealed no significant differences.

These results confirm our third hypothesis, **H3** that there was a slight increase in spatial skill score after playing with the robot, but it was not condition dependent.

4.4 Perceived Robot Mindset

All 40 children participated in the post-survey with questionnaires about Tega's mindset. The medians of the NEUTRAL and GROWTH conditions were 26.50 and 28 points, respectively. Using Mann-Whitney's U test, we found a significant effect per condition (the mean ranks of the pre- and post- tests were 16.60 and 24.40, respectively; W = 122, Z = -2.1269, p = 0.03292, r = 0.34), with the GROWTH group evaluating their robot to have a more growth-oriented mindset than the NEUTRAL group, supporting hypothesis **H4**.

5. DISCUSSION

The notion of growth mindset as formulated by Dweck [8] includes two main attributes, namely, a belief in the malleability of the brain to learn, adapt, and improve, as well as a belief in effort as a prerequisite to success. The former is highly related to the notion of curiosity, i.e. the intrinsic drive to learn [11], while the latter relates to perseverance and grit [7]. Indeed, Tega's comments and questionnaire sentences in the mindset assessment task related to the desire to learn, and the perseverance task we adopted from [22, 24] measured how children cope and continue in a challenging task.

Given the potential of social robots as peer-like companions, it behooves us to study the mechanisms by which children learn from social robots, as well as the similarities and differences between children's learning from robots as compared to human partners and other technologies. In the new paradigm explored in this work, our peer-like social robot exhibits a growth mindset in how it plays and engages with a child. The activities are also used as a probe to measure children's perseverance in the face of challenge. We examined whether young children will recognize a growth mindset of a social robot, and whether they will internalize this to influence their own. Our findings suggest a provocative new kind of relationship and interaction paradigm between children and robots, where children can identify and socially model the attributes they see in peer-like robots.

6. CONCLUSIONS AND FUTURE WORK

How children approach learning and challenge is as important as what academic skills and knowledge they acquire through education. Social robots have the potential to open new methods for how to assess and develop effective interventions that *broadly* serve children's learning skills, attitudes, and abilities.

In this work, we investigated the effects an autonomous social robot's mindset driven behavior has on a child's own mindset. Our results show that children can recognize a growth mindset exhibited by an autonomous social robot, and can socially model this in their self-reported beliefs about their own mindset, while also supporting this with consistent behaviors indicative of having perseverance.

In future work we intend to investigate the effects of long-term interaction with a growth mindset robot. We hypothesize a two-phase influence, wherein initially a growth mindset will be promoted, followed by increased learning gains. Furthermore, we intend to extend the expressive cognitive architecture of the robot to include other high-level aspects of learning, e.g., curiosity, and study the effects of such a complex architecture on children's behavior, attitudes, and learning outcomes.

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