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Exploring the effectiveness of an AI-robot-supported task-based learning approach on children's mastery motivation in preschool health education

Abstract

Physical robots could enable embodied interaction, contributing to more immersive learning environments. Embodied interactions help promote emotional connection, sustain attention, and support learning outcomes. Although many studies highlight the benefits of robots in education, their role in early childhood education (ECE) for children aged 3–8 remains largely unexplored. As children enjoy engaging with robots and often perceive them as learning companions, the use of AI robots may bring a new perspective for ECE. To maximize effectiveness, task-based learning was integrated with AI robots, encouraging children to acquire knowledge and skills by solving problems in authentic contexts. Therefore, this study proposed AI-robot-supported task-based learning in the context of preschool health education. To examine the effectiveness of this method, a quasi-experimental design was conducted with 42 Chinese children aged 5–6. Findings revealed that children in the AI-robot group demonstrated significantly higher levels of persistence and problem-solving abilities and greater emotional response. Moreover, they exhibited more active learning behaviors, suggesting that AI robots hold strong potential for fostering more effective and engaging preschool health education environments.

Keywords**:** Artificial intelligence-based robots, physical robots, TBL framework, early childhood education

Introduction

Robots, as a growing focus in artificial intelligence (AI), are increasingly being integrated into education and are emerging as advanced instructional tools (Chu et al., 2022; Socratous & Ioannou, 2022). They are typically classified as either virtual agents or physical robots (Su & Yang, 2022). Unlike virtual agents, physical robots provide embodied interaction through their tangible presence, (Al Hakim et al., 2022; Belpaeme et al., 2018), which enables more natural and immersive communication with learners (Fung et al., 2025; Rasouli et al., 2022; Yang et al., 2022). Although many studies highlight the benefits of robots in education (Chu et al., 2022; Zhang et al., 2021), their role in early childhood education (ECE) for children aged 3–8 remains largely unexplored (Chu et al., 2022; Zhong & Xia, 2020).

In the sphere of ECE, research has largely concentrated on language, science, and technology (Chaldi & Mantzanidou, 2021; Neumann, 2020; Su et al., 2023), while studies on health education for preschoolers remain scarce. Task persistence and mastery pleasure—core elements of mastery motivation—are essential for sustained engagement in early learning (Guo et al., 2023; Redding et al., 1988). However, conventional health instruction often relies on whiteboard-based, teacher-centered delivery (Mokoena et al., 2022; Ramu et al., 2022; Sabri et al., 2024), limiting children's sustained attention and hinders effective learning of health-related content (Ramu et al., 2022). Without strong mastery motivation, children tend to lack perseverance and depth in learning, especially when faced with challenges (Fung & Chung, 2023). The use of AI-robots may address these issues. Studies show that children enjoy engaging with robots and often perceive them as learning companions (Chu et al., 2022; Jin, 2019). When integrated with engaging topics and activities, AI-robots can provide timely, adaptive feedback, thereby boosting children's mastery motivation, enhancing skill development, and supporting emotional regulation (Ramu et al., 2022;

Su et al., 2023). This approach not only enriches the learning experience but also fosters positive teacher–child relationships (So & Lee, 2023).

Despite the significant potential of robots in preschool health education, practical implementation faces several challenges. Passive information delivery in classrooms can limit opportunities for creativity and imagination, thereby constraining the educational value of robotic technology (Ng et al., 2022). To maximize pedagogical value, robots must be integrated with well-designed teaching strategies (Nikolopoulou, 2023; Su et al., 2023). Task-based learning (TBL) emphasizes learning through real-world tasks, encouraging children to acquire knowledge and skills by solving problems in authentic contexts (Lin et al., 2022; Willis, 1996). Integrating AI-robots into TBL allows embodied interaction and adaptive feedback to function as learning scaffolds, thereby fostering persistence, positive emotion, and problem-solving in preschool contexts.

In summary, prior research has demonstrated the positive impact of AI-robots in early childhood education (Berrezueta-Guzman et al., 2025). However, few studies have incorporated a task-based learning (TBL) framework into AI-robot-assisted courses for preschoolers, particularly in the context of health education. To better leverage technology in enhancing children's persistence, emotional engagement, and knowledge acquisition in health-related learning, this study integrated AI-robots as technological support with TBL as the instructional framework. Based on this approach, the following research questions were explored:

(1) Can the AI-robot-supported task-based learning approach improve children's persistence compared to the traditional multimedia task-based learning approach?

(2) Can the AI-robot-supported task-based learning approach improve children's emotional response compared to the traditional multimedia task-based learning approach?

(3) Can the AI-robot-supported task-based learning approach improve children's problem-solving abilities compared to the traditional multimedia task-based learning approach?

(4) What are the differences in the learning behaviours of children using the traditional multimedia task-based learning approach and those using the AI-robot-supported task-based learning approach?

Literature Review

AI-Robots in ECE

In recent years, AI-robots have become increasingly prominent in educational research and practice (Chen et al., 2023). Early childhood represents a critical stage for sparking children’s curiosity about AI and shaping their early understanding of intelligent technologies (Su & Yang, 2022). In this context, AI-robots hold particular promise in ECE, as young children learn most effectively through play, imitation, and interaction within socially and emotionally rich environments (Kewalramani et al., 2021; Su & Yang, 2022). When equipped with capabilities such as speech recognition, natural language processing, and emotion expression, AI-robots can provide adaptive and emotionally responsive learning support that fosters children’s engagement and promotes more meaningful learning outcomes (Chen et al., 2022; Kewalramani et al., 2021; Liang & Hwang, 2023).

Recent research has increasingly emphasized the role of AI and educational robots in supporting preschool children’s cognitive and socio-emotional development. For instance, Kewalramani et al. (2021) explored how AI-enabled toys could foster social and emotional support for children with diverse needs in home-based play contexts. Drawing on the concept of emotional capital, their design-based study demonstrated that young children engaged in creative and empathy-driven dialogues with robotic toys, which sparked their joyful emotions and sense of companionship. This study highlights how AI-robotic play can promote children's social-emotional literacies by blending physical and artificial play environments. Similarly, Çakır et al. (2021) examined the cognitive dimension of AI-robot learning, investigating the effects of robotics and coding instruction on preschoolers' problem-solving and creative thinking skills. Conducted as a quasi-experimental study using the WeDo 2.0 Educational Robotics Kit, their results indicated that children in the experimental group achieved significantly higher gains in problem-solving and creative thinking than those engaged in traditional activities.

Despite the growing body of research on AI technologies in ECE, existing studies remain largely focused on the technological aspects of AI systems, such as emotion recognition, language processing, and robotics design (Su & Yang, 2022; Yi et al., 2024). However, relatively few have examined how AI-robots can be pedagogically integrated into instructional frameworks to enhance children's mastery motivation. Moreover, previous studies have primarily addressed children with special needs, leaving a gap in understanding how typical preschool learners engage cognitively and emotionally with AI-robots in domain-specific learning, such as health education. This study therefore bridges these gaps by implementing an AI-robot-supported TBL model that examines its impact on children's persistence, emotional responses, and problem-solving abilities.

The development of the AI-robot-supported task-based learning approach

Figure 1 presents the AI-robot-supported task-based learning approach, which comprises six modules: development, management, learning content, exploration tasks, interaction, and behavioral analysis. Teachers design content and task sequences in the development module and deliver them through the interaction module. The learning content module provides age-appropriate topics to establish foundational knowledge, and the exploration task module decomposes learning goals into manipulable activities. The interaction module supports tablet-based activities and robot-led guidance. The behavioral analysis module logs performance indicators such as completion time, exploration depth, and robot–child interactions. The management module coordinates four underlying databases to ensure coherent operation of all modules.

Figure 1: The structural of the AI-robot-supported task-based learning approach

The Cruzr platform was used in this study to develop AI-robots. Its development interface is shown in Figure 2. The Cruzr platform can configure tasks that robots need to complete, including gestures, facial expressions, and answering questions intelligently. During the learning process, robots can perform tasks according to the instructor's teaching plan. When a child asks a question, the robot can indistinctly or accurately identify the keywords in the child's question in a timely manner through a natural language processing system. It then searches for relevant information in the knowledge material database or large-scale online knowledge base created by the system developer and presents the corresponding learning materials in combination with voices.

Meanwhile, the robot can use appropriate gestures and facial expressions for feedback, with the main purpose of providing children with more detailed and embedded learning feedback. It is worth noting that the AI-robot system also has functions such as face recognition, face tracking, and sound source localization and guidance. When children fail in task exploration, the robot will trigger an incentive feedback mechanism. This mechanism may include a voice message paired with a gesture (e.g., "*Don't worry, Lele will be with you. Let's keep going,*" accompanied by a "hug" gesture). When children successfully complete the task, the robot will trigger a praise feedback mechanism (e.g., "*Wonderful! You did a great job!*" accompanied by an "applauding" gesture). This feedback mechanism is designed to deepen children's emotional response while promoting learning motivation. In addition, the Mugeda cloud platform is applied to design and implement the interactive animation, which not only serves as a form of learning tasks, but also provides a more attractive and participatory learning experience, thus better serving the learning process.

Figure 2: The development interface of the AI-robot-supported task-based learning approach

To organize meaningful embedded interactions of children with robots in the classroom, this study referred to the TBL framework of Willis (1996) and systematically organized the course into three stages: pre-task, the task cycle, and focus on form. Simultaneously, to create a more direct learning process, every child was equipped with a tablet. The interactive process is shown in Figure 3.

Figure 3: The learning process of the AI-robots task-based learning approach

In the pre-task stage, the AI-robot, as the supervisor, introduced the learning topic of learning about the five senses with gestures and facial expressions. (For example, robots will say with a smile, waving gesture, and friendly voice, "*Hello kids! My name is Lele, and today we are going to learn about our five sense organs together.*") The AI-robot would also review the important knowledge related to the course and the task list for this lesson by showing pictures and playing music. When children accepted an invitation from the robot to explore tasks, the robot was triggered to explain the rules to the children and guide them to complete the first task. As shown in Figure 4, the robot stood next to an interactive electronic whiteboard, which was utilized to present the learning content, guide children to review knowledge, and present specific learning tasks for the children to explore.

Figure 4: The interactive interface of the pre-task stage

In the task cycle stage, children used interactive animation with the support of robots to explore tasks with specific backgrounds and to participate in testing. There were five tasks at this stage as shown in Figure 5. Prior to each task, the robot provided the child with the context and requirements of the task. Combined with an interactive animation on the tablet, the task list and requirements were presented again. Children completed the task exploration by manipulating the tablet. During the exploration process, children could seek help from the robot, and the robot would also provide relevant learning materials according to the challenges children often encounter while learning combined with praise and motivational feedback mechanisms to help children explore the content further.

Figure 5: The task exploration interface of the task cycle stage

During the focus on form stage, the tasks in the interactive animation were combined with a task list to review the four tasks that had been completed and to help children reinforce the concepts they had learned. As shown in Figure 6, many children were encouraged and motivated by the robots to maintain positive dialogue and Q&A interactions with them. When children successfully completed all learning tasks, robots would congratulate and reward them through interactions such as dancing, hugging, and singing.

Figure 6: The interactive interface of the focus on form stage

Experiment Design

In this study, a quasi-experimental research design was employed to compare the differences among the two groups regarding children's motivation for mastery (i.e., children's persistence scale, expressive scale, and competence scale).

Participants

Two classes of children from a public kindergarten in China with an average age of 5.8 years were enrolled in this study. One class (N = 18; 9 boys and 9 girls) was assigned to the experimental group and received health knowledge instruction through the AI-robot-supported task-based learning approach. The other class (N = 24; 12 boys and 12 girls) was assigned to the control group and received instruction through the traditional multimedia task-based learning approach. The children had prior exposure to AI-robots in non-instructional activities such as temperature monitoring and entertainment, but this study marked the first integration of robots into formal health education. A post-hoc power analysis using G*Power 3.1 yielded a power value of 0.89, higher than the conventional threshold of 0.80, confirming the adequacy of the sample size (Faul et al., 2007).

In this study, group allocation was conducted at the class level rather than by random assignment of individual children. This approach was chosen to align with the practical organization of kindergarten teaching, as classes are administratively fixed and could not be reorganized without disrupting regular educational activities. While this method ensured ecological validity and feasibility, it may also introduce potential class-level influences (e.g., peer dynamics, classroom culture, or teacher–student relationships) that could affect the learning outcomes. To mitigate such bias, the same teacher supervised both groups, and each child was supported by a learning caregiver during the activities. All participating children took part in the study on a voluntary basis, following standard ethical procedures for research involving minors.

Experimental process

The experimental process is shown in Figure 7. One week before the learning activity, the teacher spent 20 minutes assisting all children in filling out the pre-questionnaire one by one. Subsequently, the teacher spent approximately 30 minutes introducing children to the application methods and rules of the AI-robots system, which aimed to ensure that the children were familiar with the learning steps and the roles of robots before the start of the learning activities. The formal learning activities began in the second week. The AI-robot-supported task-based learning approach was applied in the experimental group, while the traditional multimedia task-based learning approach was applied in the control group. The main difference between the control group and the experimental group was the lack of robot intervention in the control group. The two groups spent approximately 60 minutes each to complete their learning tasks. After the learning activity, all children participating in learning were required to complete a 20-minute post-questionnaire with the assistance of the caregiver responsible for the learning process.

Figure 7: The experimental process

Instruments

The dimensions of mastery questionnaire 18 (DMQ 18) revised by Morgan et al. (2019) was applied as an instrument; it covers three dimensions, namely, persistence scales, expressive scales, and competence scales, to comprehensively evaluate children's mastery motivation. The questionnaire was divided into a teacher evaluation version and a children's self-evaluation version, with a total of 19 items. Among them, 12 items aimed to investigate children's persistence and jointly measure their cognitive/object persistence, social persistence with adults, and social persistence with children; five items sought to investigate children's emotional response and jointly measure their mastery pleasure and negative reactions to challenge; and two items aimed to investigate their general competence compared to their peers. All three sub-dimensions were measured using the Likert scale (5 = "*exactly like this child*", 1 = "*not at all like this child*"). In the present sample, Cronbach's alpha was 0.78 for the teacher version and 0.80 for the children's version, indicating satisfactory internal consistency.

In addition, due to the low cognitive level of preschool children, they were unable to read the items in the questionnaires alone. Accordingly, the teacher introduced each question in the children's version of the questionnaire to the children, and visual aids such as Bootsma and Ciocarlan (2023) and Hall et al.'s (2016) five facial expressions from "frowning" to "smiling" were adapted to accelerate children's reactions and assist in scoring. Among them, the facial expressions from "*frowning*" to "*smiling*" corresponded to the five ordered options from "*not at all like me*" to "*exactly like me*" in the scale. When filling out the scale, children were instructed to choose a facial expression that represented their answer based on the teacher's statement of each question.

Coding scheme for learning behaviours

Two trained observers conducted the behavioral coding independently after receiving a week of systematic training on the coding instrument and rating guidelines. To assess inter-rater reliability, Cohen's Kappa coefficient was calculated to evaluate the level of agreement, yielding a value of 0.847, which indicates a high level of consistency between raters. After confirming reliability, a consensus coding procedure was adopted to ensure the accuracy of the final dataset. The coding framework for this study was developed with reference to the work of Chang et al. (2014), Yang et al. (2023), and Yang et al. (2020), and was further refined to reflect the characteristics of the AI-robot-supported task-based learning approach. The finalized scheme included 22 specific behavioral codes categorized into three major types: human–robot interaction, human–human interaction, and self-interaction (see Table 1 for details).

Table 1. Coding scheme for the children's behaviours

Classification	Code	Definition	Example
Human-robot interaction	R1	Robot guidance on learning	Children watch an introduction to the learning topics by robots.
	R2	Read the task list provided by robots	Children read the task list published by robots.
	R3	Perform the learning tasks issued by robots	Robots introduce tasks, children enter password and perform learning task.
	R4	Seek help from robots	Children seek help from robots when encountering difficulties.
	R5	Read the learning materials provided by robots	Robots provide learning materials to answer children's questions.
	R6	Get encouragement from robots	Robots encourage children to continue exploring tasks.
	R7	Other interactions	Children have conversations with robots, share experiences, or engage in interactive games.
Human-human interaction	H1	Teacher guidance on learning	Teachers introduce the learning topic.
	H2	Read the task list published by teachers	Children read the task list published by teachers.
	H3	Accept learning tasks assigned by teachers	Children enter the password provided by teachers and explore learning tasks.
	H4	Seek help from teachers or peers	Children seek help from teachers or peers when encountering difficulties.
	H5	Discussion	Children discuss learning tasks with teachers or peers.
	H6	Other interactions	Children have conversations with teachers or peers, share experiences, or engage in interactive games.
	H7	Interactions unrelated to learning	Children talk about topics unrelated to learning during the learning process.
Self-interaction	S1	Exploration of the task	Children answer questions in interactive animations.
	S2	Succeed in the challenge	Children answer questions correctly.
	S3	Failed in the challenge	Children answer questions incorrectly.

	S4	Give up the challenge	When encountering difficulties, children choose to give up and directly move on to the next step, or refuse to continue exploring tasks.
	S5	Go to the next stage	Children go to the next stage of learning and exploration of tasks.
	S6	Review learning tasks	Children return to explore previously completed tasks.
	S7	Emotional transformation	Children show more positive emotions such as curiosity, excitement, and satisfaction, or transition from negative emotions such as depression and frustration to positive emotions.
	S8	Behaviours unrelated to learning	Children exhibit negative actions such as lack of patience.

Experimental results

Teachers' ratings of children's motivation for mastery

To determine the consistency of teacher ratings for children, the pre-questionnaire scores of the two groups of teachers were analysed. The pre-questionnaire was taken as the covariate, the group as the independent variable, and the post-questionnaire as the dependent variable. The results of the analysis of variance (ANOVA) showed that there was no significant difference in the pre-questionnaire levels of the two groups of children evaluated by the teacher ($F = 2.09$, $p = 0.16$ for the persistence scale test result, $F = 2.96$, $p = 0.09$ for the expressive scale test result, and $F = 1.16$, $p = 0.29$ for the competence scale test result), indicating that the two groups of children were similar. The normality of the data was detected using the Shapiro-Wilk test, with the test results of the persistence scale being 0.98, $p = 0.70 > 0.05$, the test results of the expressive scale being 0.98, $p = 0.78 > 0.05$, and the test results of the competence scale being 0.97, $p = 0.24 > 0.05$, demonstrating that the sample in this study had normal distribution. In addition, the homogeneity test of regression slopes showed that the application of analysis of covariance (ANCOVA) was appropriate ($F = 0.04$, $p = 0.85$ for the persistence scale test result, $F = 0.01$, $p = 0.91$ for the expressive scale test result, and $F = 3.82$, $p = 0.06$ for the competence scale test result).

The analysis results of the ANCOVA are shown in Table 2. There are significant differences in persistence ($F_{(1,40)}$ = 49.47, $p = 0.000 < 0.001$), expressive ($F_{(1,40)}$ = 72.45, $p = 0.000 < 0.001$), and competence ($F_{(1,40)}$ = 21.53, $p = 0.000 < 0.001$) between the two groups. Specifically, the scores of various aspects of master motivation of children in the experimental group evaluated by teachers were significantly higher than those of children in the control group. The results showed that the AI-robot-supported task-based learning approach was better than the traditional multimedia task-based learning approach in terms of promoting children's persistence, emotional response and problem-solving abilities.

Table 2. Results of ANCOVA analysis of teachers' ratings of children's motivation for mastery in three dimensions

Variable	Group	N	Mean	S.D.	Adjusted Mean	Adjusted *SD*	*F*	η^2
Persistence scales	(1)Experimental group	18	4.63	0.29	4.59	0.09	49.47***	0.56
	(2)Control group	24	3.69	0.49	3.72	0.08		
Expressive scales	(1)Experimental group	18	4.69	0.24	4.70	0.08	72.45***	0.65
	(2)Control group	24	3.77	0.40	3.77	0.07		
Competence scale	(1)Experimental group	18	4.39	0.50	4.48	0.09	21.53***	0.36
	(2)Control group	24	3.96	0.66	3.90	0.08		

***$p < 0.001$

Children's self-evaluations of motivation for mastery

Likewise, the ANOVA results indicated no significant differences in pre-questionnaire self-evaluation levels between the two groups (persistence: $F = 2.39$, $p = 0.13$; expressive: $F = 0.20$, $p = 0.66$; competence: $F = 2.18$, $p = 0.15$), suggesting comparability at baseline. Normality was assessed using the Shapiro-Wilk test, with test statistics of 0.98 ($p = 0.61 > 0.05$) for persistence, 0.98 ($p = 0.54 > 0.05$) for expressiveness, and 0.97 ($p = 0.28 > 0.05$) for competence, confirming that the data were normally distributed. Furthermore, tests of homogeneity of regression slopes supported the use of ANCOVA (persistence: $F = 0.18$, $p = 0.67$; expressiveness: $F = 2.96$, $p = 0.09$; competence: $F = 3.60$, $p = 0.07$).

As shown in Table 3, ANCOVA results revealed significant group differences in persistence ($F_{(1,40)} = 74.70$, $p = 0.000 < 0.001$), expressiveness ($F_{(1,40)} = 63.95$, $p = 0.000 < 0.001$), and competence ($F_{(1,40)} = 106.82$, $p = 0.000 < 0.001$). Children in the experimental group scored significantly higher across all dimensions of mastery motivation compared to those in the control group. These findings suggest that the AI-robot-supported task-based learning approach enhanced children's persistence, emotional response, and problem-solving abilities more effectively than the traditional multimedia task-based learning approach.

Table 3. Results of ANCOVA analysis of children's ratings of their motivation for mastery in three dimensions

Variable	Group	N	Mean	S.D.	Adjusted Mean	Adjusted *SD*	*F*	η^2
Persistence scales	(1)Experimental group	18	4.43	0.29	4.46	0.09	74.70***	0.66
	(2)Control group	24	3.43	0.45	3.41	0.08		
Expressive scales	(1)Experimental group	18	4.57	0.26	4.59	0.10	63.95***	0.62
	(2)Control group	24	3.57	0.57	3.56	0.09		
Competence scale	(1)Experimental group	18	4.39	0.50	4.42	0.12	106.82***	0.73
	(2)Control group	24	2.77	0.51	2.75	0.10		

***$p < 0.001$

Learning behaviour

To explore the differences in the learning behaviours of the two groups of children, behavioural sequence analysis was applied to evaluate the coding data of each group of children by the calculated z-values, and a residual table for adjusting children's behaviour patterns was generated. The adjusted residual table of the experimental group is shown in Table 4. A z-value greater than 1.96 indicates that the sequence has statistical significance (Bakeman & Gottman, 1997). GSEQ5.1 developed by Quera et al. (2007) was adopted for the sequence analysis.

Table 4. Adjusted residual table of the experimental group (simplified version)

From behaviour	To behaviour(s)	Adjusted residual (z)
R1	R2, R3	14.65*, 23.49*
R2	R3	14.5*
R3	S1	25.04*
R4	R5	33.13*
R5	S2	11.58*
R6	S6, S7	4.67*, 12.32*
R7	S7	8.30*
H4	S2, S3	3.84*, 3.39*
H5	R4, H4, S2, S3	9.34*, 3.31*, 4.39*, 2.30*
H6	S7	8.52*
H7	S7	2.22*
S1	H4, H5, S2, S3	2.33*, 6.31*, 20.55*, 11.01*
S2	R6, S7	11.85*, 7.37*
S3	R4, R6, H4, H5	12.51*, 6.71*, 3.39*, 2.30*
S5	R1	32.65*
S6	S1	17.24*
S7	R7, H6, H7, S5, S6	9.74*, 10.91*, 2.33*, 13.93*, 5.66*

Note. Only significant transitions ($|z| \geq 1.96$) are reported. Full residual matrices are provided in the Supplementary Materials.

The behavioural patterns of the experimental group are presented in Figure 8. Arrows indicate the direction of sequential behaviours, with bold lines denoting transitions with z-values greater than 8.00, and thin lines representing transitions with z-values between 1.96 and 8.00. Notable transitions included S1→S2→R6→S7 and S1→S3→R6→S7, where children who succeeded or failed in task completion subsequently received encouragement from the robots, which was associated with more positive emotional expressions. Another salient sequence, S1→S3→R4→R5→S2→S7, reflected children's active engagement with robotic feedback and instructional materials, leading to eventual task success.

The observed sequences indicate that children generally followed the intended learning process of the AI-robot-supported task-based learning approach. In the pre-task stage, children reviewed knowledge points and task lists (R1→R2). During the task cycle and focus-on-form stages, transitions such as R1→R3→S1 and R2→R3→S1 reflected the progression from task introduction to task exploration. Feedback loops, as illustrated by S1→S2→R6↔S7→S5→R1, highlighted the contribution of personalised robotic feedback to sustaining motivation and promoting iterative engagement with learning activities.

Figure 8: Behavioural patterns of the experimental group

The behaviours of the control group were analysed using the same procedure. Table 5 presents the adjusted residuals, and Figure 9 depicts the behavioural patterns. In this group, the transitions represented by R1 to R3 in the experimental group were replaced by H1 to H3. Human–robot interaction behaviours, including R4 to R7, were considerably reduced. Overall, the behavioural sequences of both groups reflected a comparable adherence to the general process of the task-based learning approach. Nevertheless, children in the control group displayed additional behaviours that were not directly related to learning during teacher guidance, such as casual conversation. Instances of giving up challenges and a lack of persistence were also observed during task exploration.

Table 5. Adjusted residual table of the control group (simplified version)

From behaviour	To behaviour(s)	Adjusted residual (z)
H1	H2, H3, H7	12.17*, 18.07*, 3.04*
H2	H3	11.9*
H3	S1	24.93*
H4	S2, S3	7.71*, 7.43*
H5	S2, S3	7.34*, 4.55*
H6	S7	8.60*
H7	S7	4.03*
S1	H4, H5, S2, S3	2.05*, 2.55*, 15.47*, 7.26*
S2	S7	21.53*
S3	H4, H5, S4, S8	18.85*, 11.18*, 7.20*, 5.09*
S4	S5	4.01*
S5	H1	26.83*
S6	S1	5.76*
S7	H6, H7, S5, S6	8.46*, 2.17*, 20.03*, 5.84*
S8	H5	6.36*

Note. Only significant transitions (|z| ≥ 1.96) are reported. Full residual matrices are provided in the Supplementary Materials.

Figure 9: Behavioural patterns of the control group

Figure 10 illustrates the differences in learning behaviours between the two groups. Solid lines indicate behaviours common to both groups, dashed lines represent behaviours unique to the experimental group, and orange lines denote behaviours unique to the control group. The data suggest that children in the control group displayed distinctive behaviours such as giving up challenges (S4) and engaging in non-learning activities (S8). The behavioural path H1→H7 further indicated a decline in attention during the learning process. In contrast, children in the experimental group demonstrated positive behaviours, including seeking help from robots (R4), consulting learning materials provided by robots (R5), receiving encouragement from robots (R6), and engaging in additional interactions with robots (R7). Moreover, the behavioural paths S3→R6↔S7 and S3→R6→S6 highlighted the role of robotic feedback in helping children overcome negative emotions, persist with incomplete tasks, and strengthen their engagement. These patterns provide a potential explanation for the comparatively stronger performance of the experimental group.

Figure 10: Behavioural learning patterns of the children in the two groups

Discussion

An AI-robot-supported task-based learning approach was proposed in this study. The results of the experimental study indicated that compared to the traditional multimedia task-based learning approach, this approach can improve children's persistence, emotional response, and problem-solving abilities. Behavioural analysis further proved the effectiveness of the proposed method.

Regarding research question 1, the finding that children in the experimental group exhibited greater persistence can be interpreted through the mechanisms of timely feedback and embodied interaction afforded by AI-robots. Unlike static multimedia, the robots delivered responses in real time, which likely sustained children’s motivation when they faced challenges (Epstein et al., 2002). In fact, Leonard et al. (2023) found that children aged 4 to 6 who experienced performance enhancement were more willing to retry tasks they had not completed. In this study, when children encountered difficulties, the AI-robots functioned as both supervisors and learning partners, offering timely feedback and support through rich multimedia resources, including images, videos, and audio. This approach effectively boosted their learning motivation and, in turn, increased their persistence in task completion (Chen et al., 2020).

Many scholars have identified several specific and effective strategies for promoting state persistence in children aged 3–6 years, such as process praise, role modeling, small successes, and providing information about rewards (Alvarez & Booth, 2014; Leonard et al., 2020). Kamins and Dweck (1999) demonstrated that process praise (e.g., "*You found a good way to do it.*") is more effective than person praise (e.g., "*You are a good girl.*") in encouraging 5- to 6-year-old children to persist in challenging tasks. In the present study, the AI-robots provided feedback through appropriate gestures and facial expressions. For instance, when a child failed during task exploration, the AI-robot would use comforting speech and made a "hugging" gesture. When a child successfully completed the task, the robot would offer verbal encouragement accompanied by a "clapping" gesture. It should be noted that the definition of persistence in this study was not limited to children's persistence in performing tasks, but also included their persistence in socializing with teachers and peers. During the experiment, children are more inclined to actively communicate with teachers and express their willingness to interact with robots, which also encourages them to collaborate and negotiate with their peers. This effect may stem from children perceiving robots as learning partners and feeling excited during interactions, which helps reduce communication anxiety and encourages their willingness to collaborate with robots in task exploration. This is consistent with Deublein et al.'s (2018) research results on robots, which suggests robots can enhance students' learning motivation and promote their social interaction.

Regarding research question 2, the enhancement of children’s emotional responses can be interpreted through the socio-emotional affordances of robot-mediated interaction. Prior studies have shown that timely praise and encouragement play a crucial role in children’s emotional development (Corpus & Good, 2020). In this study, the AI-robot acted as both a mentor and a peer-like partner, providing contingent feedback, comfort, and encouragement during task engagement (Greczek et al., 2014; Chen Hsieh & Lee, 2023). Such support likely alleviated frustration, reduced fear of challenge, and promoted repeated engagement with learning tasks. In addition, children are generally more prone to anthropomorphize than adults, often attributing life-like qualities to inanimate objects such as puppets or teddy bears (Fawcett & Markson, 2010). According to Sommer et al. (2019), children tend to ascribe higher moral care to humanoid robots than to animal-like robots, suggesting that humanoid designs may elicit stronger emotional attachment. The AI-robot used in this study was the humanoid robot “Lele,” similar in height to the children, using gestures such as open-arm hugs that made several participants report feelings of warmth and comfort. This anthropomorphic design likely enhanced social presence and emotional resonance, creating a relaxed, engaging classroom atmosphere (Alam, 2022; Rossi et al., 2020). Consistent with Lin et al. (2022), the presence of a physical, expressive robot encouraged positive affective states and sustained motivation (Lemaignan et al., 2016). Nevertheless, these effects may vary depending on contextual factors such as teacher mediation, classroom dynamics, and children’s prior familiarity with robots.

Regarding research question 3, the enhancement of children’s problem-solving abilities can be explained through the constructivist features of educational robots. Educational robots essentially function as constructivist tools that enable learners to apply their existing knowledge and experience to authentic tasks and to learn through the iterative processes of developing and testing solutions (Alimisis, 2013). Within the AI-robot-supported task-based learning approach, the robot served both as a context provider and as a facilitator, generating diverse task scenarios that created opportunities for children to identify and address problems. The robot could encourage children's metacognitive engagement by asking them questions and offering guidance continuously, which led to reflection and the improvement of strategies for solving problems (Leyzberg et al., 2014; Yang et al., 2023). Through interactive engagement with the robot, children are stimulated to engage in problem solving, collaborative learning, and creative thinking (Benitti, 2012). This instructional design activates their thinking and fosters greater initiative and creativity during the learning process (Berson et al., 2023). A meta-analysis by Zhang and Zhu (2024) provides further support for this conclusion, indicating that educational robotics has a particularly pronounced influence on the development of problem-solving skills among younger learners, particularly those in kindergarten and early primary education. The effectiveness of robot-mediated learning in promoting children’s problem-solving abilities can be attributed to its capacity to integrate cognitive construction with social interaction, thereby providing opportunities for reflection and exploration. Nevertheless, this effect is not uniform; it may be moderated by contextual conditions such as task complexity, the level of teacher facilitation, and learners’ autonomy within the learning process.

Behavioural analysis indicated that, compared to children in the experimental group, children in the control group exhibited more negative behaviours, including chatting, petty actions such as lack of patience, and giving up during challenges. The reason for these differences may be that the children in the control group lacked personalized feedback mechanisms. When children in the control group encountered difficulties, they could only answer questions repeatedly or rely on answers from teachers or peers (S3→H4 and S3→H5). Such a situation will consume children's time and energy, and may also lead to negative emotions such as depression and frustration after experiencing multiple failures, gradually losing patience or giving up on challenges (S1→S3→S4 and S1→S3→S8). Yang et al. (2023) once stated that the timely feedback from robots plays a crucial role in the learning process, providing effective guidance and support for students. Considering that children need encouragement during their growth stage, it is particularly important to establish an incentive mechanism through the AI behaviours of robots (Davison et al., 2021; Melo et al., 2019). The behavioural paths of S3→R6↔S7 and S3→R6→S6 indicate that by interacting with robots, children are more likely to overcome negative moods, show greater willingness to revisit previously failed tasks, and feel more motivated to embrace challenges. Additionally, these interactions encourage increased cooperation and communication with teachers and peers, leading to more social engagement. This helps children develop good teamwork and communication skills, providing valuable support for their comprehensive development (Rosenberg-Kima et al., 2020).

Theoretical implications

Constructivism posits that knowledge is actively constructed by learners through exploration, manipulation, and situated experience, rather than passively received. Children continuously refine their cognitive structures through iterative processes of assimilation and accommodation in interaction with their environment (Jones & Brader-Araje, 2002). TBL, as a representative practice of constructivism, situates learning within authentic, goal-oriented tasks that transform abstract concepts into concrete and manipulable activities. This approach facilitates learner-centered and socially oriented classroom development (Long & Porter, 1985; Willis, 1996).

Social interaction theory further underscores the social dimension of learning, emphasizing that children acquire cognitive and emotional support through communication, collaboration, and dialogue with peers, teachers, or more experienced individuals. Through language, imitation, and feedback, they gradually develop cooperative and emotional regulation abilities, thereby maximizing their potential within the zone of proximal development (Topçiu & Myftiu, 2015; Williford et al., 2013). Within this framework, the teacher's role shifts from a transmitter of knowledge to a designer and facilitator of learning tasks, who regulates task difficulty and mediates collaborative conflicts to sustain learner-centered practice (Littlewood, 2004; Skehan, 1996).

When TBL is integrated with AI-robot support, the robot's real-time feedback provides individualized guidance that enhances the precision of children's exploratory learning, while its anthropomorphic interaction features extend the task context to form a multidimensional "child–robot–peer" interaction network. This integration helps to overcome the traditional limitations of TBL in sustaining interaction and engagement. By predesigning AI-mediated interaction strategies and regulating the instructional pace, teachers can ensure that learning activities align with children's cognitive developmental trajectories, thereby promoting the coordinated growth of cognition, emotion, and social competence through human–AI collaborative learning (Kim, 2024).

Practical implications

In this study, AI-robots effectively supported children's knowledge construction and mastery motivation development during TBL through real-time feedback and personalized guidance. However, the current level of technology still constrains their educational function. Robots cannot substitute for teachers' essential roles in providing socio-emotional support, value orientation, and classroom culture building (Chan & Tsi, 2023; Istenič et al., 2024). Overreliance on robots in educational practice may weaken teacher–child relationships and diminish teachers' central position in emotional accompaniment and social development (Istenič & Rosanda, 2021).

Therefore, future applications should emphasize a “human teacher–robot” collaborative model, where teachers act primarily as emotional facilitators and learning regulators, while robots focus on cognitive scaffolding and operational support. Such functional complementarity can better align technological and pedagogical strengths (Huang et al., 2023).

From a technological perspective, although multimodal robots demonstrate greater immediacy of interaction and contextual immersion than traditional multimedia tools, they still face practical constraints such as high costs, complex maintenance, and insufficient teacher training (Neumann et al., 2023). Without institutional mechanisms and sustained resource investment, their educational value may remain limited to pilot implementations rather than long-term integration. Thus, future research and practice should explore sustainable implementation frameworks that ensure both pedagogical continuity and technological feasibility (Ryalat et al., 2025).

Furthermore, cultural and social contexts play a mediating role in shaping children’s acceptance of educational robots (Kim et al., 2021). Cross-cultural studies suggest that cultural values significantly influence how children perceive robots’ educational roles. In Confucian-oriented contexts, the cultural notion of teacher authority leads children to attribute greater legitimacy to human teachers, often resulting in cautious or restrained interactions with robot teachers, while showing stronger engagement with peer-like robots that align with egalitarian and collaborative learning norms (Li & Yow, 2024). In contrast, children in cultures that emphasize autonomy and critical thinking display higher acceptance of robot teachers and greater initiative in human–robot interaction (Tazhigaliyeva et al., 2016). Such cultural variability may, in turn, affect learning motivation through differences in interactional engagement (Zaga et al., 2015).

Beyond technological and pedagogical considerations, issues of equity and ethics warrant closer examination. Access to AI-robot technologies remains uneven across preschools, particularly between urban and rural contexts, which may exacerbate existing educational inequalities if not accompanied by equitable funding, infrastructure, and teacher training. Moreover, as AI-robots increasingly engage in social and affective exchanges with children, educators and policymakers should remain critically aware of how such technologies may shape children's perceptions of empathy, autonomy, and social responsibility. Addressing these equity and ethical concerns is essential to ensure that AI-robot integration contributes to inclusive, sustainable, and socially responsive early childhood education rather than reinforcing new forms of digital divide.

Conclusions and future suggestions

This study demonstrates that the AI-robot-supported task-based learning approach can significantly enhance preschool children's mastery motivation, emotional response, and problem-solving abilities in health education. Compared with prior early childhood robot studies that treated robots primarily as stand-alone teaching aids, and with non-robot TBL interventions that lacked mechanisms for personalized feedback, this study demonstrates the distinctive pedagogical contribution of integrating AI-robot support within TBL. The findings establish a replicable instructional model that fosters persistence and meaningful learning outcomes in preschool health education.

There are also several limitations to this study that should be addressed.

First, group assignment was conducted at the class level rather than by individual randomization. Although this procedure aligned with the practical constraints of kindergarten settings, it may have introduced class-level biases that reduced internal validity. Future studies could adopt randomized or cross-class assignment strategies to better control for such effects.

Second, the participants were children from a public kindergarten in China where AI-robots had already been integrated into daily play activities. As a result, many of the children were familiar with interacting with robots, which may limit the generalizability of the findings. Future studies should therefore replicate the intervention in more diverse cultural and institutional contexts to examine its applicability across settings.

Third, the procedures of this study were time-intensive, and the final number of valid participants was relatively small. To address this, future studies could employ more efficient methods to record and organize children's learning processes, and include larger samples to enhance statistical power and representativeness.

Fourth, although the health education activities were conducted in small groups, this study did not focus on evaluating individual engagement or performance within group contexts. Future studies could incorporate more comprehensive measurement approaches, including assessments of teamwork, academic performance, and socio-emotional development. Longitudinal and qualitative approaches, such as extended classroom observations and interviews, would also provide deeper insights into changes in learning behaviors over time.

Finally, future research should also consider equity issues, such as whether children from different socio-economic or cultural backgrounds benefit equally from robot-mediated learning. Addressing these questions will strengthen the robustness and inclusiveness of the AI-robot-supported task-based learning approach in early childhood education.

Competing Interests

The authors declare no competing interests.

Data Availability

All anonymized datasets and analysis materials supporting the findings of this study are publicly available as supplementary materials accompanying this article. These materials include the raw questionnaire dataset, SPSS analysis syntax, variable codebook, behavioural sequence datasets for both experimental and control groups, the behavioural coding framework, and a methodological note detailing the parameters used in the sequential analysis conducted with GSEQ 5.1. All identifying information has been removed to ensure participant confidentiality.

Ethical approval

This study was reviewed and approved by the Committee for Human Research of East China Normal University, China (Approval No. 20240116, approved on 16 January 2024). The scope of the approval covered all research procedures involving children's participation, data collection, and data analysis. All procedures performed in this study involving human participants were conducted in accordance with the ethical standards of the institutional research committee and with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

Informed consent

Written informed consent was obtained from the parents or legal guardians of all participating children before the study began. Members of the research team explained the study's purpose, procedures, potential risks and benefits, data handling methods, and participants' rights to the parents or guardians. They were informed that participation was voluntary and that withdrawal was possible at any time without any adverse consequences. Considering the young age of the participants, verbal assent was also sought from the children in an age-appropriate manner.

Consent forms were distributed and collected in December 2024 at Jiangbin Kindergarten in Fujian, China. All data were anonymized prior to analysis, and no personally identifiable information was retained or disclosed.

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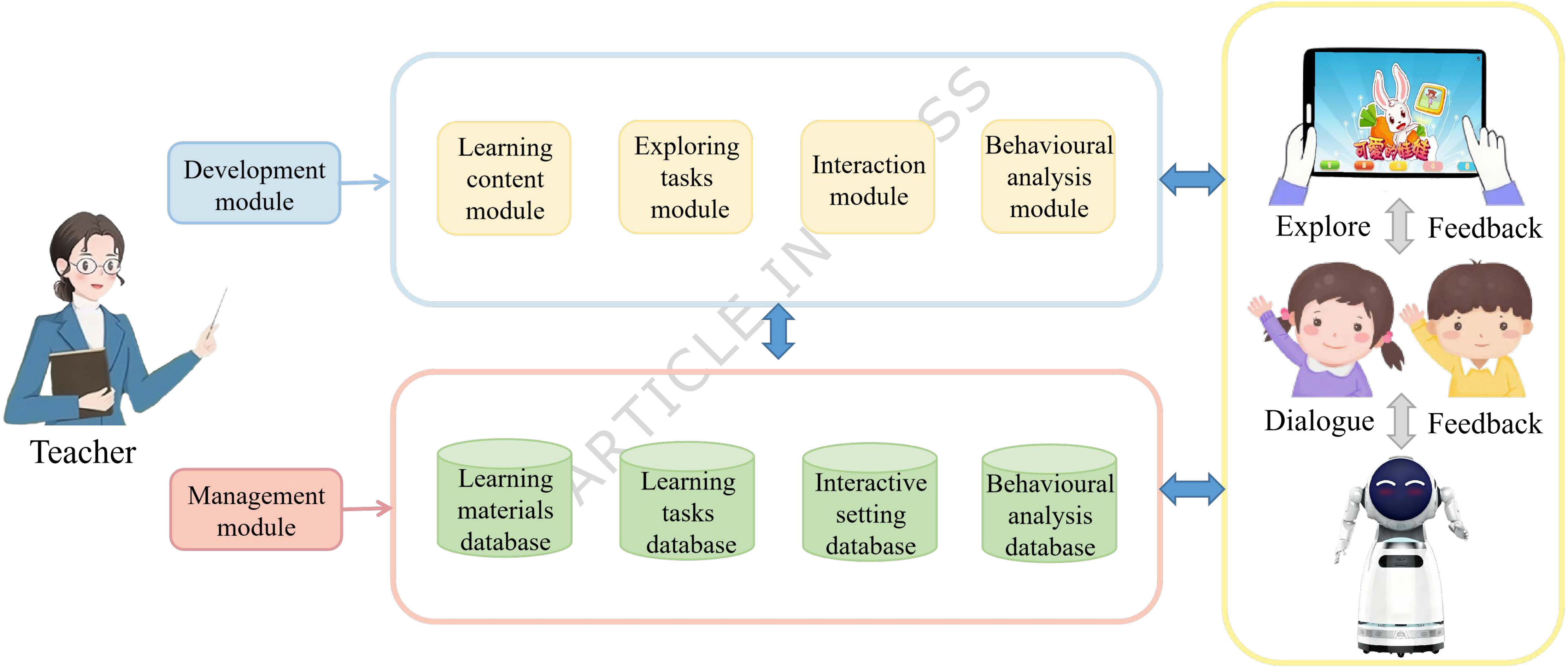

Development module
Learning content module
Exploring tasks module
Interaction module
Behavioural analysis module
Teacher
Management module
Learning materials database
Learning tasks database
Interactive setting database
Behavioural analysis database
Explore
Feedback
Dialogue
Feedback

Examples of tasks

Emotion: “ Love ”

Gesture: “ guide to left ”

Answer: “ Kids, you are so capable! We have finished recognizing all the five senses today. Next, draw a picture on the tablet and design a beautiful and handsome child. Now please enter the password 1234 to start the last level! ”

TTS 小朋友们，你们真是太能干了呀！我们今天都认识

Emoji Love Motion gui...
TTS 小朋友们，你们真是太能干...

Emoji Grin Motion gui...
TTS 小朋友们，学习了保护五官...

Emoji Shy Motion sea...
TTS 小朋友们，你们知道怎样保...

Emoji Happy Motion sha...
TTS 小朋友们，学习了五官的功...

Emoji Smile Motion sha...
TTS 鼻子可以闻很多味道，花朵...

Emoji Music Motion sha...
TTS 耳朵可以听到很多声音，听...

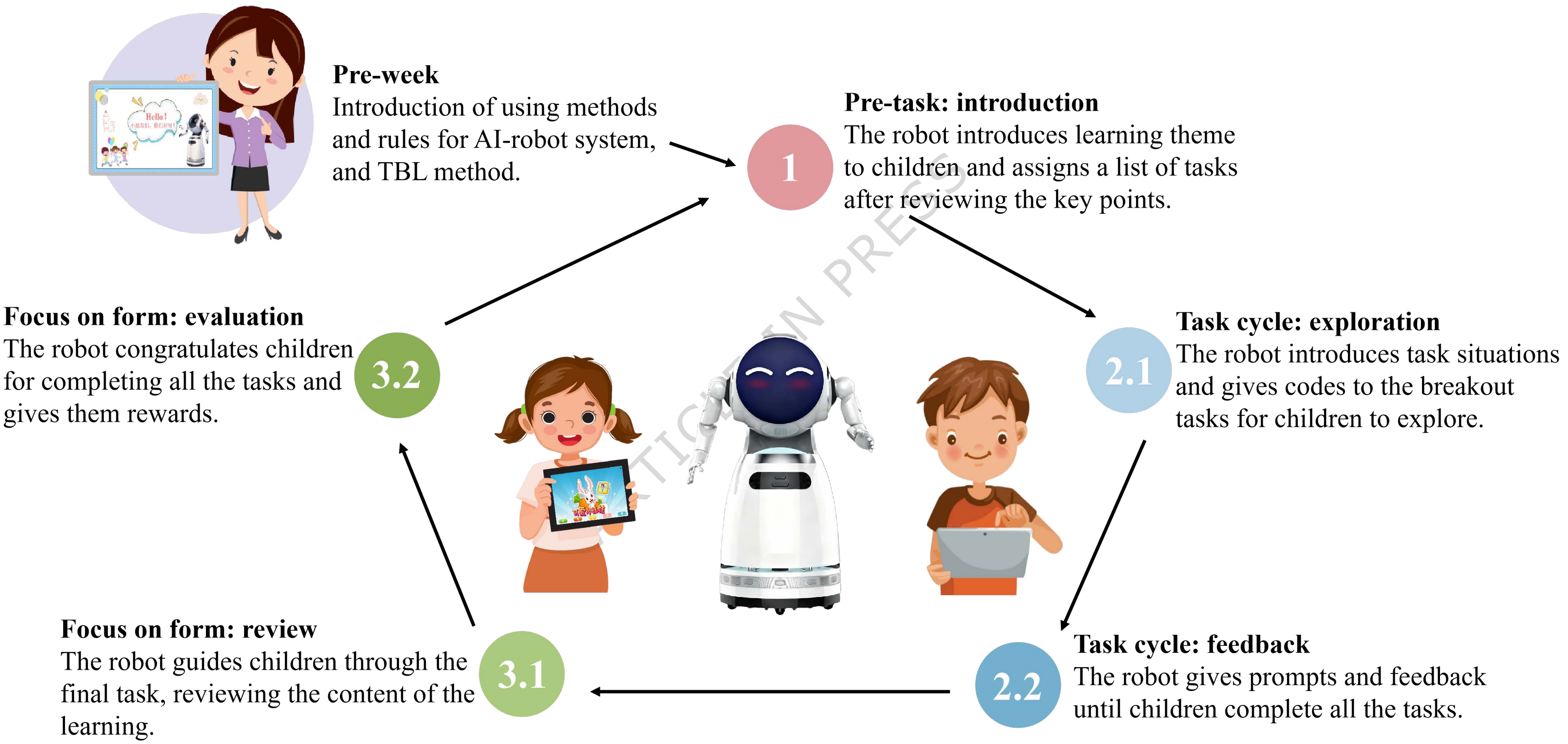
Emoji Wron... Motion nod
TTS 眼睛可以看电视、看书。眼...

Emoji Proud Motion sur...
TTS 眉毛让我们拥有很多表情，...

Emoji Shy Motion sha...
TTS 小朋友们，你们知道每个五...

Emoji Naug... Motion swi...
TTS 小朋友们，都完成任务了吗？

Emoji Smile Motion gui...
TTS 好棒呀，那么接下来就是第...



Pre-week
Introduction of using methods and rules for AI-robot system, and TBL method.

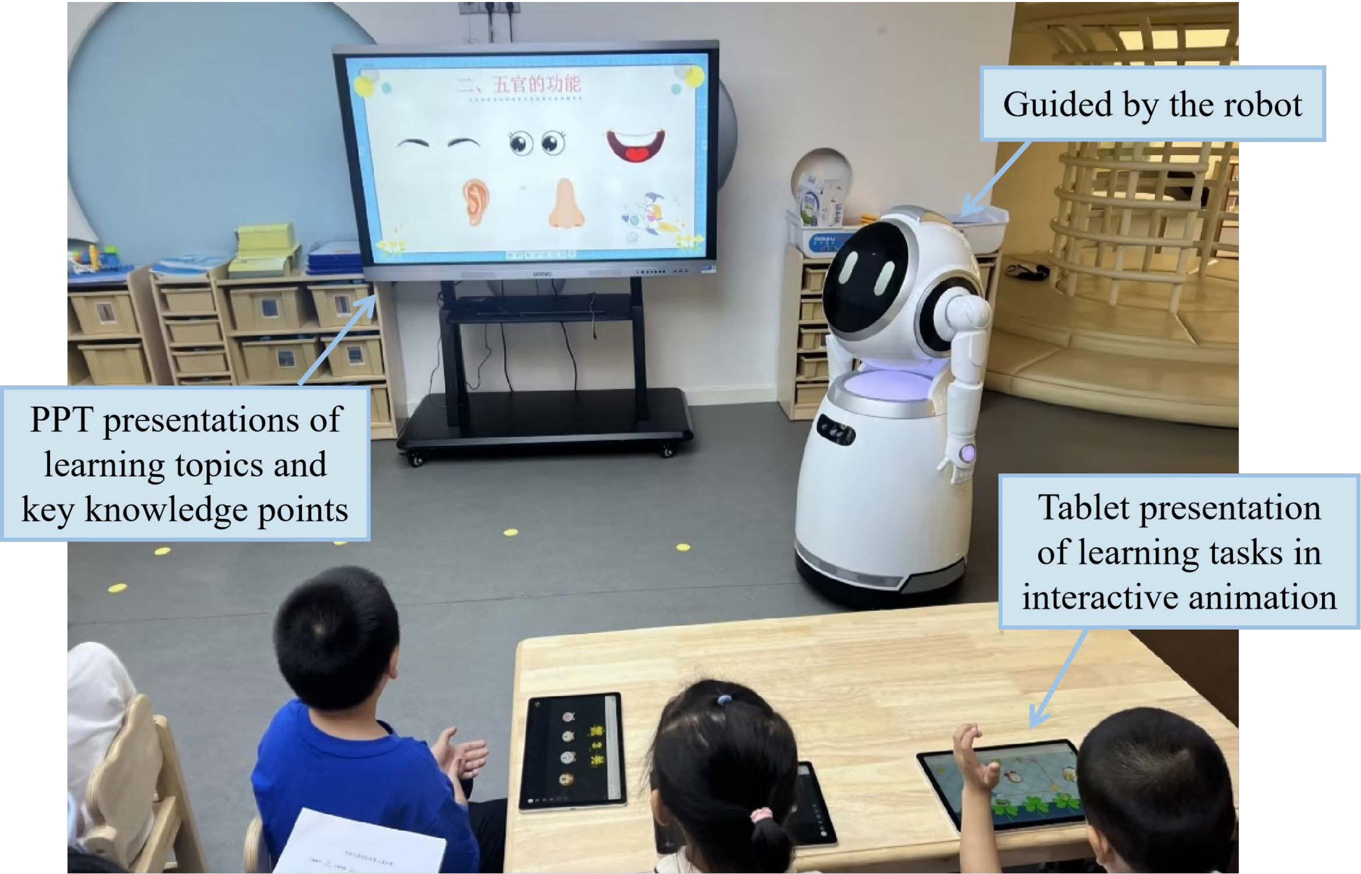
Pre-task: introduction
The robot introduces learning theme to children and assigns a list of tasks after reviewing the key points.

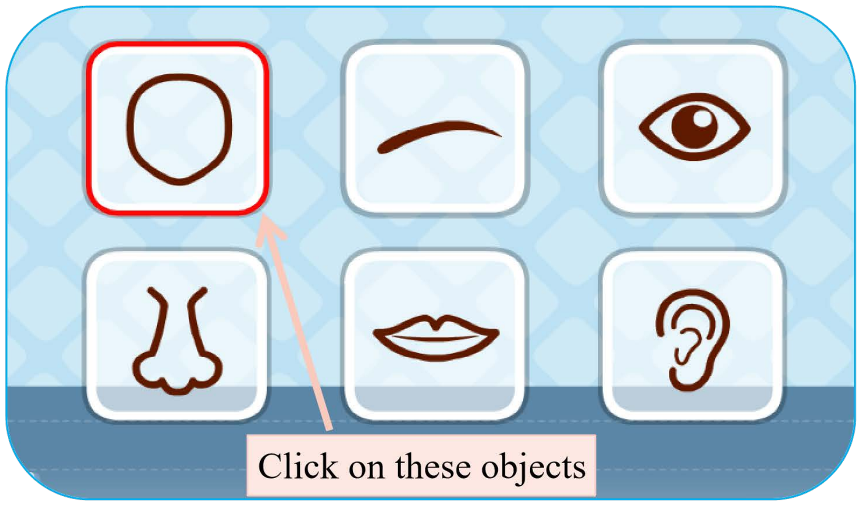
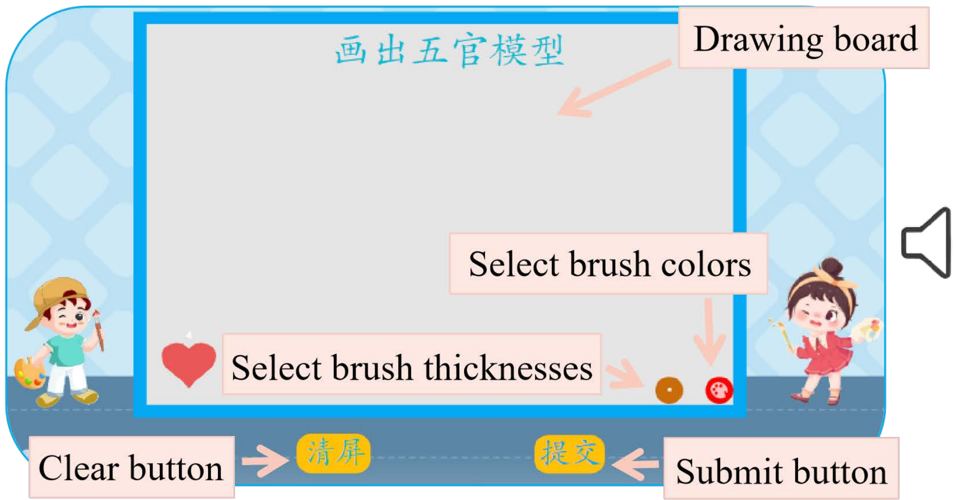
Task cycle: exploration
The robot introduces task situations and gives codes to the breakout tasks for children to explore.

Task cycle: feedback
The robot gives prompts and feedback until children complete all the tasks.

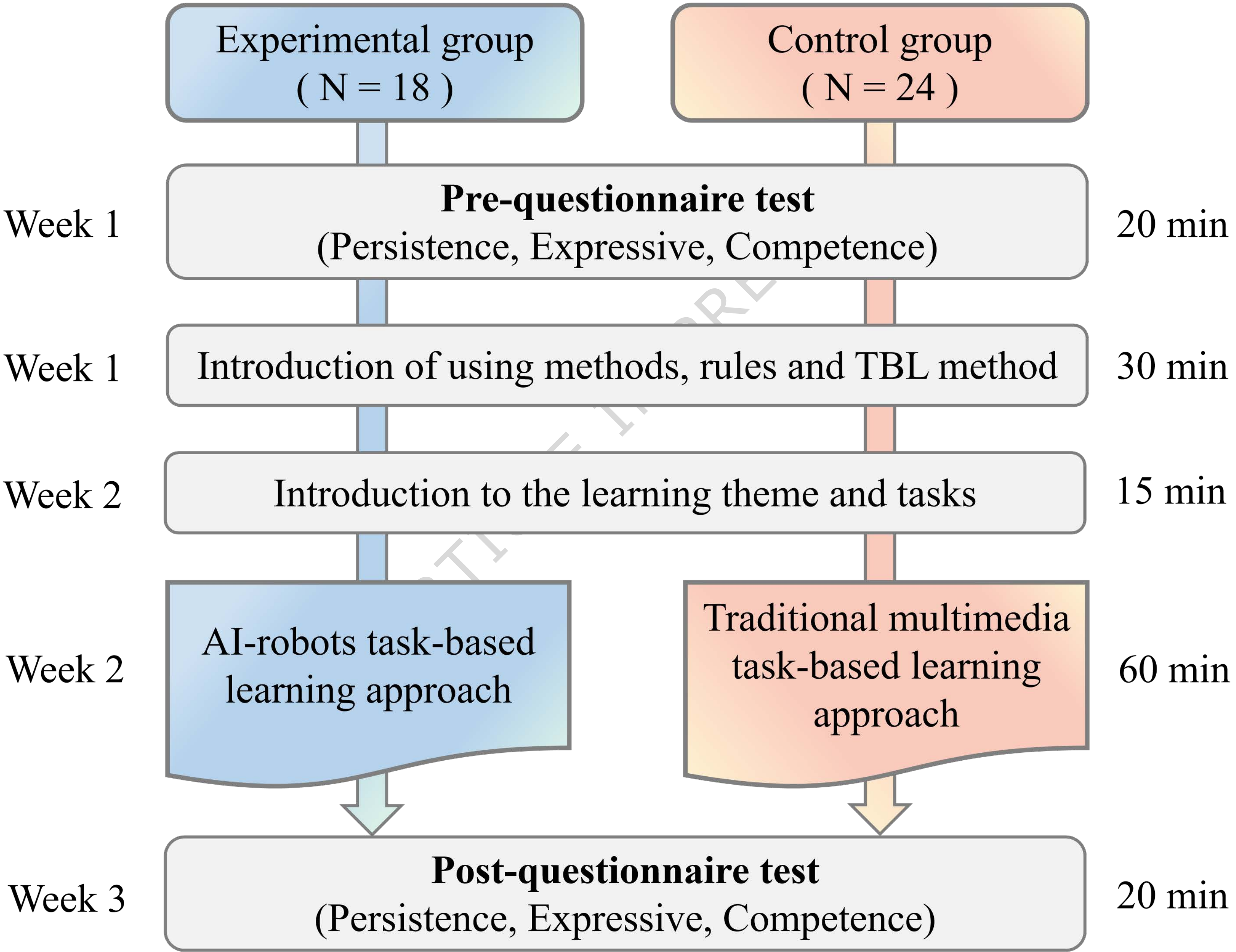
Focus on form: review
The robot guides children through the final task, reviewing the content of the learning.

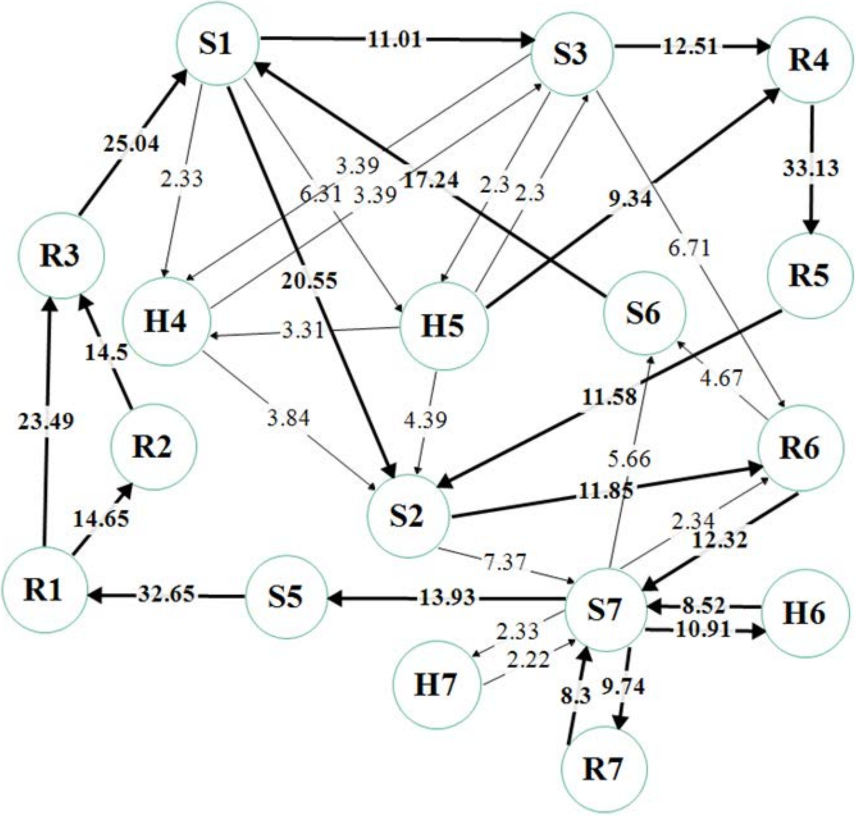
Focus on form: evaluation
The robot congratulates children for completing all the tasks and gives them rewards.


二、五官的功能
Guided by the robot
PPT presentations of learning topics and key knowledge points
Tablet presentation of learning tasks in interactive animation

	The interface for task exploration	Children will hear	The learning process
Task1		Children, please help the kid in the animation to find the appropriate five senses. (1)Head. (2)Brows. (3)Eyes. (4)Nose. (5)Mouth. (6)Ears	Guided by the system’s voice, children need to click on the object. When they successfully select the correct object, an eye-catching red border will appear and the correct sound effect will be played.
Task2		Children, please help the kid in the animation to put the pictures together.	Children need to drag the objects on the left to fill the model on the right. When they succeed in placing an object in the correct position, the object will remain in the model and will be played with the name of the corresponding object.
Task3		Children, please send the animated children to the correct leaves. (1)Three children are singing happily. which of the five senses is functioning?	Asked by the system's voice, children need to drag objects and place them in the leaf sorting house. When they succeed in placing the correct leaf, the system will play the correct sound effect and add a star.
Task4		Children, which of the kids in the animation is the good boy who protects the five senses, pick him out!	Children need to click on the pictures in the animation to choose which child is using the right way to protect the five senses. If they choose correctly, the system will play a sound with the correct effect and a happy kitten will appear.
Task5		Kids, what do your five senses look like? Pick up your brushes and draw!	Children can choose their favorite brush color and brush thickness to draw their own five senses model on the drawing board, and submit it to the teacher management system.

Children talk and interact with the robot, which gives them feedback and accompanies them in reviewing key points


Experimental group
(N = 18)
Control group
(N = 24)
Week 1
Pre-questionnaire test
(Persistence, Expressive, Competence)
20 min
Week 1
Introduction of using methods, rules and TBL method
30 min
Week 2
Introduction to the learning theme and tasks
15 min
Week 2
AI-robots task-based learning approach
Traditional multimedia task-based learning approach
60 min
Week 3
Post-questionnaire test
(Persistence, Expressive, Competence)
20 min


S1
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R4
R3
H4
H5
S6
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R2
R1
S2
R6
S5
S7
H6
H7
R7
11.01
12.51
25.04
2.33
3.39
6.31
3.39
17.24
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2.3
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6.71
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3.31
14.5
11.58
4.67
23.49
3.84
4.39
5.66
11.85
14.65
2.34
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32.65
13.93
8.52
10.91
2.33
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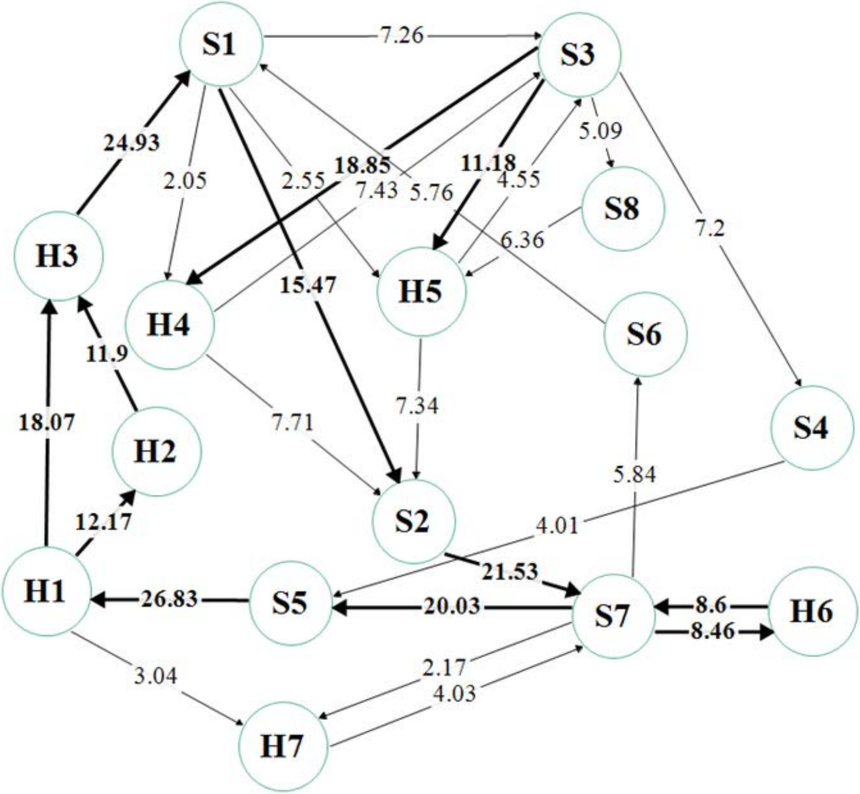
8.3
9.74


S1
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H2
S2
H1
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7.26
24.93
2.05
2.55
18.85
7.43
5.76
11.18
4.55
5.09
7.2
6.36
15.47
11.9
18.07
7.71
7.34
5.84
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21.53
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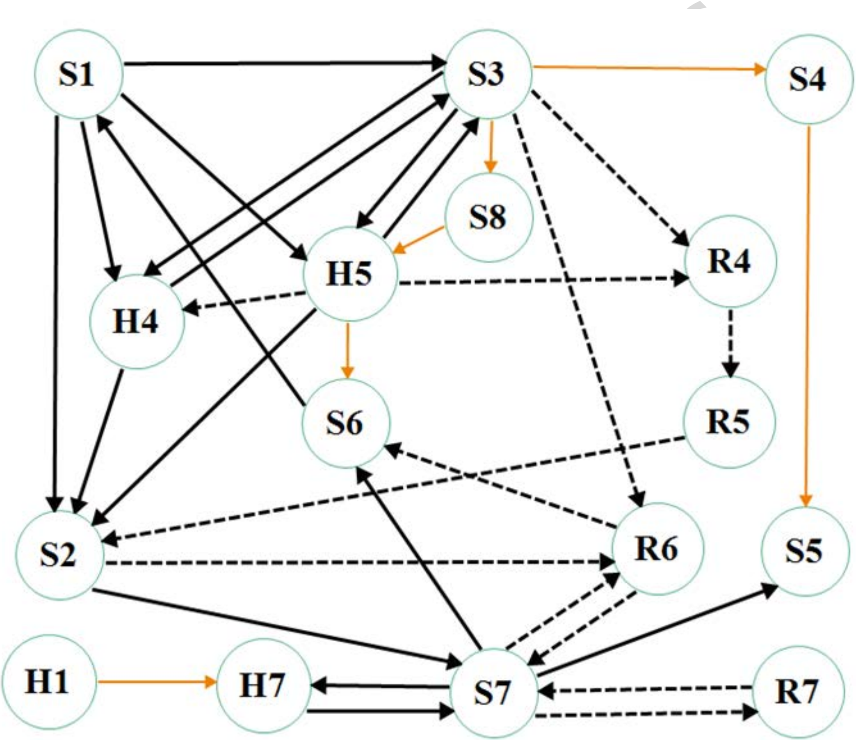
S1
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H1
H7
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