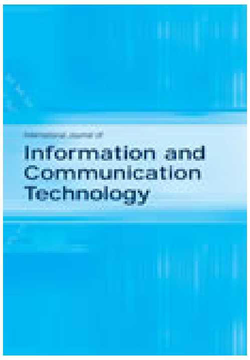

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Research on intelligent teaching curriculum of preschool education majors in universities based on artificial intelligence technology support

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Research on intelligent teaching curriculum of preschool education majors in universities based on artificial intelligence technology support

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Abstract: Using the PopBots toolbox, children can construct, design, experiment, and play with their very own social machine, all while learning basic AI concepts. However, children have not been taught whether to use or develop this modern technology. This article developed PopBots to assist children aged 4 to 7 in their education by integrating constructionist principles into an AI-based programme. Early childhood education is one area where the use of robotics (AI) in the classroom has recently garnered significant attention. The aim of the research was to explore how schools can better prepare their early childhood learners with AI-based intelligence learning programmes. The research findings demonstrated that AI technology can provide students with more personalised learning experiences and enhance the overall quality of education. This research contributes to the development of an intelligent teaching curriculum for university-level pre-kindergarten education majors.

Keywords: artificial intelligence; technology; preschool education; virtual reality; knowledge-based system; supervised machine learning; SML.

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Biographical notes: Yabo Yang studied at Shaanxi Normal University from 2008 to 2011 and obtained her Master's degree in 2011. Since graduating in 2011, she has been working in preschool education and teaching; she has been working as a full-time teacher at Xi'an Translation Institute since 2013. In recent years, more than ten papers have been published in Chinese journals, mainly focusing on the research areas of preschool education curriculum and teaching, preschool integrated education, and preschool information technology education.

1 Introduction

The educational sector has not been immune to the revolutionary effects of machine learning (ML) (artificial intelligence – AI). There are now more ways than ever before to provide students with individualised and contextualised instruction, as well as smart and effective testing and evaluation of their progress. Its utilisation of AI-based tools in the early childhood classroom has gained traction in past decades argue by Ding (2021). The preschool years are crucial because they set the tone for the rest of a child's training and growth. As a result, it is essential to investigate how AI technologies might bolster the early childhood curriculum in higher education. The purpose of this research is to examine how colleges can best help students majoring in early childhood education create an intelligent instruction course using AI innovation. This research delves into the advantages of using AI in the classroom and recommends a programme layout that incorporates AI-based tools and strategies to improve the standard of kindergarten education. Younger adolescents greatly benefit from having a sociable robot as a learned partner, and we discovered that this was the case. We also pinpointed instructional strategies that were most helpful to our pupils (Yu and Luo, 2022). We use these to suggest improvements to the PopBots system in future versions. Even more preschoolers are enabled to utilise electronic material and activities thanks to emerging AI-enabled platforms that facilitate engagement via action, contact and voice. But preschoolers cannot yet comprehend the functionality of AI-enabled products like intelligent toys. They must, though, in order for kids to utilise them in a positive and secure way. While more and more courses are being developed to teach candidates basic AI, the vast majority are designed for college-bound students or graduates, and even fewer are accessible to those without programming experience. As a result, we developed a syllabus for teaching preschoolers about AI via the process of creating, programming, training, and interacting with their very own socialising machines.

According to Weiwei (2022), people who discover AI later are going to have a very distinct perspective on intelligent devices compared to those who grew up around them. Little ones may use the PopBots platforms, including instruction, which includes one socially robotic toolkit, several interactive AI exercises, and related evaluations, to educate about and experiment with machines studying logic, including creative techniques. This document presents the evaluation research's findings and details specific instruments we created for working with children age's 4 to 6. We looked at the way children of different ages and sexes engaged with the PopBots toolbox elements and how that affected their grasp of AI concepts. We expected that young people's engagement with the toolkit, rather than criteria like age or proficiency in technology, would decide how much they learned.

1.1 Intelligence meets kids

You now carry around machines inside your hands as well as robotics in your living spaces. IPads and gadgets available for kids as young as one year old today have much more processing capacity than most people's desktop machines had just a few years ago. Whether kids conceptualise AI-enabled gadgets as intellectual, behavioural, and human beings depends on a variety of variables, including their own backgrounds and perspectives as well as social and cultural expectations (such as how their parents discuss technology). Their perceptions regarding AI gadgets improve as they develop experience with and knowledge of such tools (Liu and Wang, 2021). As future generations are raised alongside smart devices, the ability to effectively use technology will be crucial. According to previous research, kids do not comprehend how advanced technology, like smart toys, functions. Children often share secrets with imaginary robots without understanding that the gadgets may record their talks, according to a study of children's use of smart toys. Studies on children's compliance have also shown that smart toys may affect and mislead young children who are too confident in the gadgets. Our objective is that educators and parents can help kids form a positive and balanced perspective about AI by providing them with practical lessons that shed light on the inner workings of this technology.

1.2 Instruction using AI

Learning about AI involves more than just learning what machines process; it also involves learning how they make logical sense, reason, acquire knowledge, produce, see and interpret. Programmes that allow learners to develop and evaluate systems based on AI and methods are available at the university level (Tian and Cui, 2022). Higher-level AI programmes stress the value of learners creating their own initiatives. Robotics is often used in these classes to help participants visualise concepts. Younger kids, who tend to be more tangible in their thinking and more physically engaged in their learning, greatly benefit from hands-on methods in Science, Technology, Engineering, Math's (STEM) education. As a social and emotional being, a social machine is a valuable tool that we use in our work with children.

2 Literature review

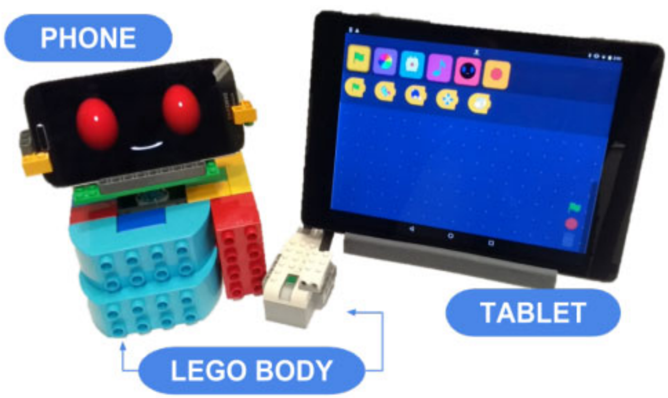
The possible advantages of using AI technologies in educational settings were extensively studied and researched (Tang and Hai, 2021). In particular, there has been a lot of focus on how to use AI tools in kid-friendly settings like preschools. The use of AI in the form of smart educational structures, chatbots, and digital agents has been the subject of many recent investigations that have shown promising results for improving the quality of instruction in early childhood settings (Ma, 2021). Moreover, studies have demonstrated that using AI equipment in the classroom might boost learners' involvement, motivation, and opportunities for studying. In order to better prepare future early educators, this literature review will analyse previous studies that have investigated the efficacy of AI technology in the early years of schooling. By showing kids that 'it is very essential above all that studying is enjoyable', she created the initial framework for teaching computerised tomography (CT) in 1974 using TORTIS. Machines, instructional applications, web pages, cards, and equipment are just some of the modern options for kids aged 4 and above. Through a variety of activities, problems, and creative projects, kids can acquire mathematical concepts like organisation, stipulations, disintegration, and so forth. The original AI curriculum was heavily influenced by the engineering of these types of learning-to-code platforms (Alam and Mohanty, 2022). Kids learning are optimised by repetition, interaction, and socialising computing concepts, according to studies conducted on different CT systems. Training and tests were developed to accompany the knowledge in a box (KIBO) machine, and the results showed that even very small kids could acquire computer reasoning; nevertheless, they require additional repetitions to fully grasp the concepts. Using a tactile interface, kids might 'teach' the robot an accepted practice by composing an application by arranging stickers on papers and presenting it to the machine. Researchers discovered that by anticipating the robot's mental state and 'educating' its emotions and interpersonal abilities, students were able to examine computing ideas through an interpersonal lens (Jiang, 2021).

2.1 Programme redesign using PopBot

According to Liu et al. (2020), as a result, we included constructionist thinking in our AI programme. These four ideas form the basis of our designs:

1. Training with one's hands create an immersive toolbox where kids can choose their own adventure.
2. Education from beginning to conclusion get kids involved in the whole process, from education to running the finished device.
3. Honesty and competence pick methods and provide feedforward that reveals as many underlying cognitive processes as feasible.
4. Attempting something new creatively combine AI technology with imaginative play. Allow kids to take charge and create anything they care about.

Figure 1 PopBot parts (see online version for colours)



Notes: The cellphone, building bricks, drives, and detectors make up a sociable robotic. A tablets is home to the blocks-based coding environment.

Source: Adopted by Williams et al. (2019)

Any mobile device running the PopBot software plus a device running the Pop-Blocks application form the basis for the PopBot system (shown in Figure 1). To make coding accessible to kids who are not able to read quite yet, all of the components are illustrated (Liao and Gu, 2022). Instruments for detecting motion, closeness, sunlight, contact, and voice are all included in the robot's input modules. Command functions like pauses and looping are also supported by special blocks. The robot can be programmed to do certain tasks, but it also has enough autonomy that it can perform tasks on its own and explain its logic to the student (Liao et al., 2021). As an illustration, a robot's independent 'mind' allows kids to look at where different algorithms are at right now. The device also keeps track of the time, the game the kid is playing, and any controls he or she taps.

2.2 Educating for AI

To help kids realise robots may become innovative like humans, we utilised PopBots to introduce them to information structures, controlled computer studying, and creative AI

(Liang et al., 2021). The extent to which younger infants can grasp such ideas is unknown.

2.2.1 Informed techniques

Conventional forms of AI, called information-based networks (or specialist networks), typically include two primary elements: a means of representing information and a mechanism for acting on that representation (Alam, 2021). Youngsters may get an understanding of the way robots may acquire and utilise information for later decision-making by studying expertise networks. Figure 2 depicts the interface kids use to teach the robot rock-paper-scissor's three guidelines in the system based on knowledge exercises. When kids are done programming the robot, it will repeat the specifications and return to the students. The robot may be taught both right and wrong by the kids (Yang et al., 2022).

Figure 2 Image captured from the rock-paper-scissors game (see online version for colours)

The machine is going to say, 'I believe you, please, are going to put X, so I am going to place Y since Y defeats X' if its prediction for the next play is more accurate than a chance (33%). If the youngster is doing well, the machine will remark something like, 'I am becoming great at this', which will hopefully inspire them to continue going. The more that you use me as a pawn, the greater we will become (Yang et al., 2020).

2.2.2 Discover machines with human help

Customised recommendations on YouTube Kids use guided algorithmic intelligence. It needs to be learned through samples. This article shows kids why robotics acquires designs from practice sets (Xu, 2021). These tasks teach the machine to categorise good and harmful meals by attributes. The device has been programmed using data regarding 20 items, including hue, dietary category, energy per 100 g, and glucose per 100 g. Meal categories and colours received proximity-based numbers. Fruits were more like vegetables than cheese. Managed AI employs k closest neighbours for k = 3. 'I have not figured out where everything belongs yet', the machine says if nothing is tagged (Li, 2022). The method used only matches the nearest meal when the total amount of identified products is less than k. Figure 3 shows children teaching the robot to detect good and bad meals. Users may programme the machine's meal response. The AI says, 'X is a lot like Y, so X goes in the exact same group as Y'. A help request lets kids ask the machine for clarification on its food categorisation. To see whether a robot identifies items, kids may change the amount and variety of meals inside the training kit (Ye and Sitthiworachart, 2022).

Figure 3 Supervised machine learning (SML) user picture (see online version for colours)

Notes: Toddlers drag meals into the nutritious or harmful boxes to rate him. Kids taste meals via touching on.

3 Methodology

Our research used a combined methods strategy to probe the creation of an AI-assisted smart learning programme for pre-kindergarten teachers at colleges. A review of the literature analysis, deep conversations with subject-matter experts, and an online poll made up the method used. In the first stage, we did an extensive literature review to find research that looked at the application of AI in regards to teaching young children. A review of the literature was conducted to determine the current AI-based techniques and approaches that may be utilised to enhance learning and instruction in early settings, along with the possible advantages and limitations of incorporating AI into early childhood education. The next part of the research was deep conversations involving several AI and educational experts. The conversations were conducted to better understand the present status of AI in preschool learning, the obstacles to incorporating AI within the educational programme, and possible gains for children and educators. The interviewees' insights were crucial in shaping the course content and ensuring its relevance to the latest developments and difficulties in the sector.

3.1 Methodology of the evaluation

For the purpose of assessment, we implemented the programme as a weeklong unit in both pre-kindergarten (typically ages 4–5) and elementary (typically ages 5–6) settings. The curricular evaluations were used to evaluate the students' grasp and retention of the subject. Information gathered from children's interactions with robots at various points throughout the school year we utilised these two kinds of data to analyse how the children's training, growing older, level of contact, and quantity of contact with the toolset influenced their evaluation score.

A total of five classes at four distinct institutions were examined throughout the spring of 2018 (Table 1). Eighty kids between the ages of 4 and 6 were surveyed. Two of the classes were located in commercial educational institutions, and the remaining third is part of an official after-school programme. The pre-kindergarten population was concentrated in just two classes. Both pre-kindergarten and kindergarten students were enrolled in class E, whereas all pre-kindergarten students resided in class A. A pupil in class D played Minecraft 3, one pupil in class C utilised a Brick We-Do, and the kids in class B spoke about robots in class, so they all had some prior knowledge about robotics and computing. Automation and other cognitive methods of thinking were not mentioned by any of the rest of the kids.

Table 1 Attendees by years old, identity and class

Factors		*Total %*
Years old	3	8 (10%)
	4	47 (58.8%)
	6	25 (31.2%)
Identity	Girls	38 (47.1%)
	Boys	42 (52.5%)
Class	Early-kindergarten	27 (33.8%)
	Kindergarten	53 (66.2%)
Total		80

Table 2 Social breakdown of the participants

	ED (a)	*ELL (b)*	*Average years*	*Identity*	*N*
A	N/A		4.71	20.00%	16
B	N/A		6.03	28.75%	23
C	11.20%	8.90%	5.47	22.50%	18
D	52.10%	38.70%	5.7	8.75%	7
E	36.70%	52.40%	7	20.00%	16

Note: Take into account the percentage of the student body that is (a) economically deprived (ED) comprised of (b) English linguistic learners (ELLs) and kids from low-income families, as determined by the combined annual earnings of the student's parents.

3.2 Process

The duration of every event was around 10 to 15 minutes. Participants completed AI assessment tests right after every class. The study included the investigator displaying an image and reading the query loudly. Investigators seldom interacted with children as they replied on their own using screens or a notepad. We filmed the lessons on video, gathered information on how the kids used the materials, and logged their answers to the examination items along with the quantitative information that we collected through the evaluations and tablet logs. Students often collaborated with an ensemble of 4 or 5 classmates in a learning environment. The duration of the exercises was adjusted for each class according to the instructors' individual demands. Over the course of five days, lessons were taught in rooms C through E. Since we were given just two days to spend in each of schools A and B, we packed a lot of content into those short periods of time. Due to time constraints, only half of class B was able to finish the AI generative task. The fact that some kids were missing did not really matter as the events were not sequential, but that created another issue.

4 Results and discussion

Performance in validating the point of view AI evaluations was determined by the percentage of items answered correctly. Using chi-square analysis on test questions and one-way ANOVA tests on testing averages, we compared how well pupils performed on standardised exams based on year and class, ethnicity, and class. Then, we analysed young people's tablet interaction records to determine the frequency and duration of each activity. Sections unique to each task. We averaged the data from the tablets across schools since students often worked in different groups. The Pearson correlation coefficient was computed to investigate the link between students' regular tablet use and their test scores.

4.1 D/F in year old, class and identity

As can be seen in Table 3, in general, we observed that adults did better than the younger children on the tests. Pre-kindergarten students averaged 58.7% on all ten inquiries, whereas K students averaged 70.8% (F = 6.54, p = 0.013). Pre-kindergarten kids often did better than kids across the board. Students in kindergarten had a significantly lower mean score than those in Grade K (63.3% vs. 76.8%, F = 5.88, p = 0.018) on the information-based systems assessment (items KB1-4 on the rock-paper-scissors activity). Keyboard button 3: 'The computer believes that Sally is going to play papers next'. This is where things diverged the most. How will the robot best Sally at a game? Only on this issue did the gap between pre-kindergarten (58.3%) and K [85.4%, 2 (2, 65) = 4.594, p = 0.032] students widen significantly. Nearly 40% of pre-kindergarten kids got it wrong, with 'rock' being among the most frequent erroneous responses. A child's explanation of why the machine would be playing rock since that is its favourite kind of game hints that kids who were younger may not have been ready to make the connection between the robot's forecasts and the way it would think about what motion to play subsequently.

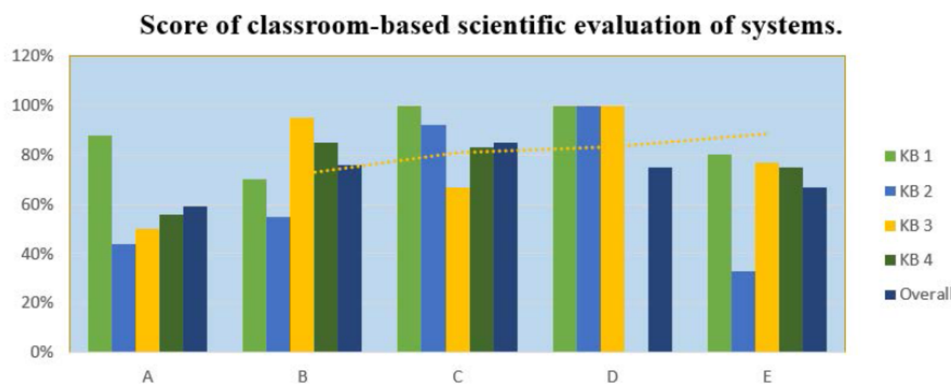
Questions SL1–3 from the food categorisation activity's guided ML exam revealed wide variation in students' grasp of closest neighbour relationships (SL2). While over 90% of children aged 5 and 6 correctly answered this question, just 25% of children aged 4 did so [2 (2, 55) = 14.164, p 0.01]. K students had a considerably higher rate of accurate responses [97.6% vs. 38.5%, 2 (1, 55) = 25.385, p 0.01] on this question compared to pre-kindergarten students. Only 45% of kids of all ages guessed correctly on SL1's 'You launch the machine and put fruits and vegetables into the beneficial group'. For which category does the machine assume chocolate belongs? Which faction are we to believe is the evil one? Age had a negative correlation with correct answers [2 (2, 55) = 8.623, p = 0.013].

Last but not least, the kids all did poorly on the GM test (GM1–3, the remix activity). Young children only appeared to notice the simplest example (GM1, 83.3%), which is that when music is played to the robot, it will play back a tune that normally sounds different. GM3's "Does the robot's song have to have a few of its identical sounds as the input?" was the weakest of the bunch. The fact that just 14% of kids got this one right indicates that the exercise probably had the opposite effect of what was intended. No age-related changes in response frequency were found. Furthermore, we did not uncover any statistically noteworthy gender disparities across the tests.

Table 3 Knowledge-based (KB), SML, generative music (GM), evaluation outcomes broken down by age and grade level are shown statistical significant at the = 0.05

Factors		*KB*	*SML*	*GM*	*Total*
Years old	5	57.2%	67.1%	57.3%	54.9%
	7	74.0%	74.3%	43.9%	65.4%
	3	79.0%	70.5%	54.4%	71.6%
	F	1.75	0.41	6.17	0.157
	p	0.41	0.742	0.814	0.412
Class	Early-K	64.2%	64.3%	55.3%	57.6%
	K	71.6%	72.3%	54.9%	72.3%
	F	5.51	3.87	0.162	6.45
	p	0.018	0.0651	0.547	0.013

Figure 4 Class-level results on the KB system exam as administered to the students (see online version for colours)

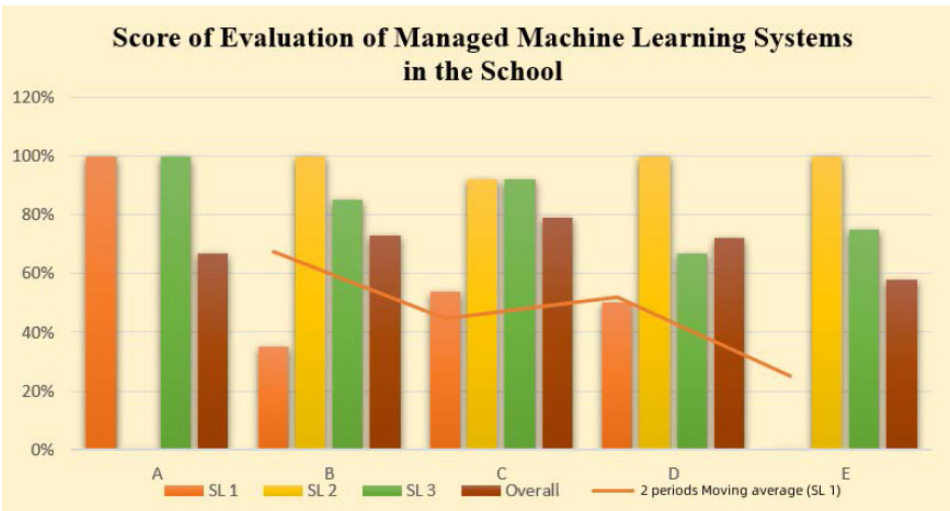


Note: Every learning environment is represented by a single point on the line graph.

4.2 Distinctions based on tablets use in the education

Just a few of the evaluation items showed significant variations based on age as well as grade. But when we compared their tablet use to their performance on standardised tests, we observed significant discrepancies across the classrooms. While students in rooms C and D completed all activities together and shared a single tablet and robot, students in the other rooms studied in small teams or pairs using their own robots. The score of classes C and D was significantly higher than that of the other classes on question KB2 [2 (2, 65) = 13.48, p 0.01]. This is probably because the youngsters had more opportunities to study the device's forecasting processes as they took turns handing along the touchscreen device. The length of time youngsters spent playing rock, paper, scissors versus the robot was weakly associated (rS = 0.40) with their evaluation score. Time devoted to playing with the robot was also positively correlated with answering KB3, a further query concerning the robot's predictive abilities (rS = 0.7). On KB4, which asked the robot to apply the opposite of what it had been instructed, there was a similar positive correlation between learning and development time and getting the response right.

Figure 5 Group rankings based on students' results on a ML-supervised exam (see online version for colours)



Note: In Figure 5, we can see the overall school average.

While the other classes worked in small groups, students in rooms C and D conducted all of the activities together, sharing a single tablet and robot, forming robot-equipped teams or classrooms. Classes C and D performed considerably higher than the remaining classes on question KB2 [2 (2, 65) = 13.48, p 0.01]. The reason for this is probably because the youngsters had more opportunities to study the machine's forecasting processes as they took turns handing around the tablet. The length of time youngsters spent playing rock, paper, scissors versus a robot was weakly positively correlated (rS = 0.40) with their evaluation score. Time spent competing versus the robot was also positively correlated with answering KB3, a further query concerning the robot's predictive abilities (rS = 0.7). On KB4, which asked the device to apply the opposite of what it had been that was covered, there was a comparable high link between education and code as well as getting the response right.

We observed that experimenting with different lesson sets for the guided ML exercise had a significant impact on the kids' grasp of the material. Poor performance on SL1 was shown in classrooms B through E, which asked how the robot classified things when presented with just positive samples. Training with and testing large quantities of foods had a significant detrimental effect on test scores. We found that kindergarteners taught the robot as many meals as possible without testing it, whereas pre-kindergarten schools spent more time trying various training sets. This increased the likelihood that the pre-kindergarten pupils would find the initialisation scenario that SL1 investigates. Studio A, which consisted entirely of pre-kindergarten students, performed the worst on question SL2. We first assumed that younger kids would have a tougher time with this question. However, in pre-kindergarten classroom E, every single student got this question right.

Thus, the majority of kids in classroom A selected the wrong response, 'banana', which drove the apparent age-related skill gap. A fruit like a tomato and a banana both have their eggs on the interior, so that kid reasoned, This shows that, contrary to a failure to grasp the AI idea, the low mark may have been the result of being taught about vegetables and seeds at some point earlier in the year. Lastly, the majority of children barely understood parts of the 'GM exercise', except for roughly half of those enrolled in room D. The primary distinction in school environments the main difference between D and the other classes was that students in D created their own music for the robot instead of only using pre-programmed tunes. If participants had recorded a new song, they could have paid more attention to the melodies they were playing than to what the robot was playing back.

Children were exposed to three areas of AI via the process of creating, instructing, and controlling a social robot. When there were numerous levels of reasoning involved, such as in the information-based systems exercise, we saw that children's ages had an effect on their comprehension. We also found that kids did better on tests when they were given more time and direction to go deep into various activities. This study does more than just show how to make AI ideas understandable to kids; it also covers important issues of design for future AI curriculum aimed at non-programmers with little expertise in automation. For our games, we had the kids break down their approaches to addressing issues into basic concepts that could be easily conveyed to the robot. At last, they saw how the robot's brains integrated basic concepts into complex actions. This means that the AI algorithms that run the robot may be understood by people who are not programmers thanks to the use of simple and familiar analogies. The goal of future research should be to assist educators in designing a curriculum that can be modified to fit the requirements of a wide range of learners. The kids were taught by an automaton that rationalised its actions. More exposure to the robot's thinking led to a deeper understanding of the topics for kids who performed additional matches against it. The ability to question the system with 'why did you do this or that?' has been shown to improve student learning. Multiple studies have shown that a child's understanding of computer programming concepts improves with more sensory input. These three applications of AI were selected as a starting point because of the rapid and obvious cycle of feedback they use. Not all intelligent concepts are as straightforward, nevertheless, so we need to figure out how to build exercises around the ones that are not so obvious.

5 Conclusions

Additionally, there has been plenty of discussion lately regarding how intelligence could be utilised in educational settings, as multiple studies have examined different ways of demonstrating AI principles to students. In this study, we provide a unique computational toolbox and curriculum for teaching AI to young children, centred on the use of a programmable social robot. The research set out to create a toolset for teaching AI principles to kids and then evaluate how well it worked. Many sociable robots formed the heart of this computing toolbox, interacting with kids in a variety of ways to teach them about fundamental AI techniques, including supervised instruction, unsupervised instruction and rewarding education. Students may learn about programming and robotics by directing a robot to carry out a variety of activities and seeing its reactions to data as part of the course. Forty-two youngsters, ages 6 to 8, participated in the research and played alongside the robotic device for 15 minutes. The findings showed that the youngsters had an acceptable understanding of several ideas related to AI after just 15 minutes of involvement. The kids' level of AI comprehension increased in proportion to the depth of their exploration of the ideas via the activities. This shows that teaching youngsters about AI through activities that include interaction and play might help them grasp the subject.

Results are encouraging, but additional research is needed to produce a successful AI curriculum that covers more information and can be adaptable to various situations, such as classes with more mature, non-programming students and non-expert instructors. The computational tools and curriculum introduced AI ideas to young learners; however, they may not be ideal for advanced or non-programmers. Thus, a more inclusive AI curriculum is needed. The research also suggests hands-on approaches to teach young children AI principles including planning, observation, reasoning, and deep learning. AI literacy empowers youngsters to use AI technology to build projects and improve reasoning and metacognition.

The research affects AI curriculum design. The research emphasises hands-on, conversational AI education. Such methods let students experience AI ideas, which improve their comprehension and memory. Second, the research demonstrates that programmed social machines can interest adolescents in AI ideas. A pleasant and interactive system like the one used by the social robot may motivate kids to study. In conclusion, a computational toolset and curriculum that guide young children's AI inquiry using a programmed social robot shows promise. The research suggests that hands-on or interactive AI learning might help youngsters comprehend AI ideas. However, further study is required to produce an AI curriculum that covers more content and can be modified for older, non-programming pupils and non-expert instructors. An excellent AI curriculum could empower students with the ability to read, encourage them to build AI projects, and improve their logic and metacognition. This study impacts education. AI literacy and concepts are crucial for young learners as AI and technology become more important in society. Using programmed social robots to teach AI may help students gain confidence and proficiency in AI technology. This might create a new breed of thinkers and problem solvers who can handle complicated challenges and define AI's future.

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