Cluster Comput (2016) 19:987–999
DOI 10.1007/s10586-016-0558-9

Teachers' views on the use of robots and cloud services in education for sustainable development

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Received: 25 August 2015 / Revised: 14 March 2016 / Accepted: 15 March 2016 / Published online: 2 April 2016
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Abstract Various studies have shown the educational use of robots to be effective in science and mathematics education. However, such studies have not considered the psychological factors affecting users of the new technology, only external factors, such as the range of affordable robotic platforms and ready-for-lesson materials for a robot-assisted learning environment. It is necessary to extend the use of robots and cloud platforms to support education for sustainable development. To that end, this study first assessed the possibility of using robots in education for sustainable development by providing them to children from low-income families, since they often show abnormal behaviors and have few opportunities to access robots in education. The long-term changes in their behavior resulting from this outreach program were examined. Qualitative as well as quantitative methods were used to evaluate and discuss the changes in self-efficacy and learning attitudes of students during the year. Second, we proposed a technology acceptance model, termed RSAM, for teachers in robot-assisted learning environments with a cloud service platform. Acceptance factors were estimated using a weighted average method based on teacher focus group interviews. The challenges associated with robot-assisted learning considering cloud services are discussed.

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Keywords Education for sustainable development · Cloud services · Robot outreach education · Technology acceptance model · Robot-assisted learning

1 Introduction

It is well known that hands-on education, such as robot assembly and creative robot construction, provides more powerful motivation than the learning of abstract knowledge, and STEM (science, technology, engineering, and math) education may expand with new educational tools based on robotics [2,35]. STEM-related industries are expected to show steep growth over the next decade compared to non-STEM related industries. However, students' interest in STEM-related jobs and careers has been decreasing. The proportions of females, African Americans, Hispanics, Native Americans, and possibly Asian-Pacific islanders participating in STEM-related industries are expected to be relatively low [3]. To solve this problem, there has been world-wide effort to promote various types of STEM education. Among them, as a tool to increase students' interest in science and technology, robots have been actively used in many countries, including the U.S., Canada, England, Germany, France, Korea, India, Israel, Mexico, and Chile.

However, to make effective robotics education possible, several obstacles must be addressed. Mataric et al. (2007) listed several challenges that must be overcome to engage a child's interest in STEM, such as the lack of affordable robot kits, the lack of ready-for-use lesson materials, the lack of age-suitable academic materials, the lack of teacher time, and the lack of teacher training [25]. In spite of the advantages of robot education, the high price of robot kits also often limit youths from low-income families from accessing the educational opportunities necessary to learn and practice these skills. Related to this trend, robot studies have generally targeted average students, whereas only a few studies have targeted low-income students [20,33].

The goal of Education for Sustainable Development (ESD) is to allow every human to acquire the knowledge, skills, attitudes and values necessary to shape a sustainable future. It also requires participatory teaching and learning methods that motivate and empower learners to change their behavior and take action for sustainable development. ESD consequently promotes competencies such as critical thinking, imagining future scenarios, and making decisions in a collaborative manner [37]. Although outreach of robotics may fall within the ESD category, due to the expense of robot kits, not many attempts are being made to implement their use. Dias et al. (2005) examined robotics as education for sustainable development in Sri Lanka, Ghana, and the USA [9]. Several universities have supported various robotics-centered outreach activities for students from low-income families with few opportunities [10,17,22,28,32,33]. Similarly, in Korea, most students from low-income families who are housed in child welfare facilities supported by the government have difficulty receiving services, and so paying tuition and buying a robot kit can be prohibitively expensive for them. Moreover, it is estimated that many students who are housed in child welfare centers and who have participated in such experiments have learning disabilities and/or ADHD (Attention Deficit Hyperactivity Disorder).

In this study we conducted a 1 year outreach program using robots for students from low-income families and performed qualitative and quantitative analyses to determine its effect on 112 students who show abnormal behaviors, such as ADHD in Sect. 3. In Sect. 3.1, social officers' views of children from low-income families who received ESD through education involving robots for one year are qualitatively observed and we provide a quantitative analysis based on long-term evaluations of changes in learning attitudes, as a reflection of students' self-efficacy in mental health areas in Sect. 3.4. We also propose and estimate a TAM (Technology Acceptance Model), termed RSAM (the Robot Service Acceptance Model), of 267 teachers under the cloud service platform in a robot-assisted learning environment in Sect. 4. It shows the barriers preventing the spread of robots in learning and teaching environments and the challenges are discussed.

2 Background

2.1 Robotic education

Goodrich and Schultz (2007) classified educational robots into two categories, assistive and educational robots [11]. Han (2010) also divided them into two categories: hands-on robots (also referred to as educational robots) for STEM education, and educational service robots (also referred to as assistive robots) such as those for language learning [12]. This paper focuses on hands-on robots.

The use of robots in education is known to increase students' interest in STEM areas as well as their problem-solving abilities and creativity [31] while also promoting active exploration, cooperative group learning, frequent interaction and feedback, and real-world connectivity [16, 19]. Studies have shown that students are willing to participate outside of school to learn with robots [2,33], and robots have been shown to increase the interest of female students in STEM education [39]. Barker and Ansorge (2007) compared the pre-test and post-test scores of students who attended robotics education with those of students in a control group. The results revealed that the students who used robots in class had significantly increased mean scores on the post-test [2].

In the twenty-first century, the primary focus of the world's major countries on ESD is on narrowing the gaps in educational opportunity and performance. In the U.S., 39 % of all students are from low-income families, and 62 % of all parents have no education beyond high school, with Latinos and African-Americans accounting for 54 % of the total [9]. Most students from low-income families who have been exposed to poor living and economic conditions show low confidence, low self-efficacy, and low concentration abilities. These characteristics can lead to low school grades, which in turn results in low school entrance rates, forming a vicious circle of poverty.

On the other hand, it is well known that when students gain confidence in one area, it can affect other areas of performance, and improve the rate of success experienced by the students. From such gains, confidence can improve self-efficacy. It has been reported that students with high self-efficacy as adolescents show low unemployment rates and are highly satisfied with their jobs [29]. Faith and self-confidence acquired during a student's adolescence can affect not only their school life but also their future job success.

Various outreach programs for students from low-income families are being operated around universities with the goals of increasing their educational opportunities, their motivation to undertake a science education, and their heath knowledge, among other areas. For example, the Stanford Medical Youth Science Program (SMYSP) works to increase knowledge about the sciences and health professions, and offers guidance about the college admissions process to low-income and/or underrepresented minority students [36]. Evaluations of SMYSP have shown that the university- and school-based programs have been highly successful in reaching low-income students and preparing them for medical and other careers.

ESD programs, such as outreach programs using robots, are also being attempted by universities and companies to

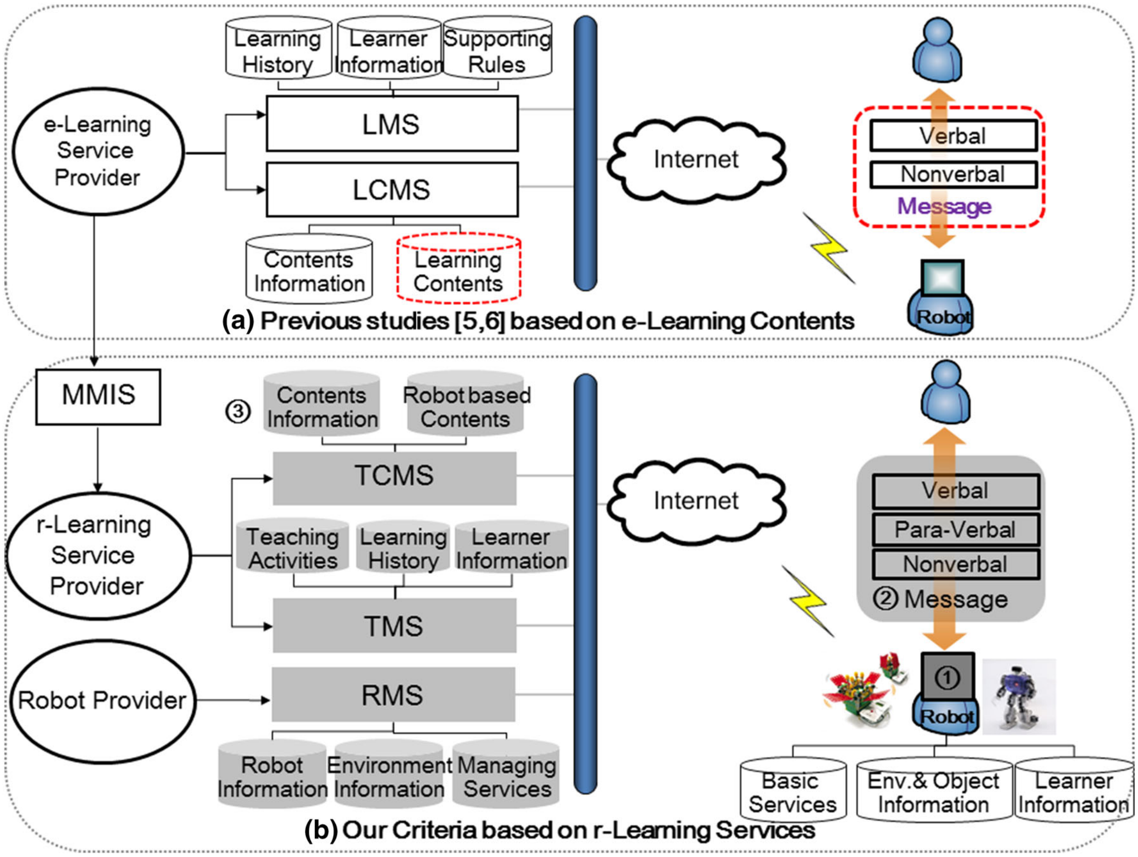


Fig. 1 Comparison of previous and our criteria in the r-Learning service framework [12,13]

narrow the gaps in educational opportunity and performance stemming from the gap between rich and poor segments of society, thus integrating society and increasing its growth potential. Dias et al. (2005) conducted an ESD study with robots as a solution to global poverty [9]. Salamon et al. (2011) did not observe any differences in performance levels between low-income students and middle-income students with respect to teamwork, programming concepts, and support in a robot outreach program [33]. If the approach could be freed from the cost of the robot kits and the cost of robot training camps, robot outreach programs are likely to be meaningful as an ESD program.

2.2 Human robot interaction in a cloud environment

Cloud computing is a promising paradigm that provides ready-for-use lesson materials for robotics education. In order for cloud service providers to meet their quality of service objectives, it is important to examine how software architectures can be described to take full advantage of the capabilities introduced by such platforms [4,24]. r-Learning services are defined as pedagogical and interactive activities which can be reciprocally conducted for interaction between learners and robots in both real and virtual worlds [12]. The r-Learning service framework can adopt types of cloud based distributed applications that are identified from [4], or social learning platforms based on collective intelligence from the interactions between students, teachers and robot in an educational environment from [18].

An r-Learning service framework from (b) of Fig. 1 is typically based on a cloud environment in the same style as e-Learning services with an operational environment. These are known as the Learning Management System (LMS) and the Learning Contents Management System (LCMS), as shown in (a) of Fig. 1 (see [12] in detail)]. It consists of the Teaching Management System (TMS), which is a symmetrical point to LMS; the Teaching Contents Management System (TCMS) to LCMS, and Robot Management System (RMS). LMS does not depend on the device type (computer, lap-top, smartphone, and etc.) but robots have copious nonverbal messages through their various appearance-hardware. Since the r-Learning service framework is assumed by numerous robots, not just one robot, RMS is needed to manage the robots from various robot providers. TMS in the r-Learning service framework may recommend context-aware personalized resources from TCMS according to the learners' historical sequential patterns in [23]. However, the robot based contents of TCMS are quite unlike any other e-

Learning resources which can be made by such multimedia tools for distributed synchronous cooperative providers, as mentioned in [34]. The robot based contents are linked to a number of robot hardware platforms.

In face to face communication, the channel can be omitted from Berlo's SMCR (Sender-Message-Channel-Receiver) model [1]. The *message* is the idea, opinion, emotion or information conveyed by the sender. It includes various things like language, gestures, body language, and whatever contents the sender speaks from beginning to end. According to the law of Mehrabian, there are basically three elements in any face-to-face communication: *verbal message* (words), *paraverbal message* (e.g., tone of voice), and *nonverbal behaviour* (e.g., facial expression); these have also become known as the 7–38–55 %, based on their relative impact. Specifically, *the nonverbal* component is 55 % of the total impact, with the balance comprised of facial expression (35 %) and body language (20 %) [26].

Choi et al. (2012) and Choi et al. (2013) divided the message into three categories, which are colored red broken lines as shown in Fig. 1a: *verbal message*, *nonverbal message*, and *visual learning contents-message*. They considered visual learning contents (photos, videos being downloaded or uploaded) to be a type of message, and then proposed three assessment criteria: *visual learning contents-message* based on computers, *verbal messages* (speech recognition abilities, attention, questions, instructions, learning error correction feedback, and motivation reinforcement feedback) [5], and *nonverbal messages* (gestures, facial expressions, semi-verbal messages, distances, physical contact, interfaces and time) [6].

However, their studies only focused on the message and did not examine the robot as a sender in the Sender-Message-Receiver model. As a sender, the robot is the one who transfers the information to the receiver after carefully putting its thoughts into words or visual contents. The robot has to possess *communication skills*, *attitude* towards the receiver based on his/her information and learning history, and *knowledge* about the subject one is going to communicate. These features may be distributed in a cloud environment of the r-Learning service framework as in (b) of Fig. 1, nonetheless their criteria have been suggested without a cloud platform, with respect to the r-Learning service framework.

To create new assessment criteria for robot assisted learning, it is necessary to define a Human Robot Interaction (HRI) model. Considering the distributed features of the robot, our HRI model consists of four factors: *Robot-Cloud Environment-Message-Receiver (Human)*. The *cloud environment* deals with the robot's information, the learner's information, learning history, and so on. The *message* includes all the contents in the class the robot gives, such as words, visual learning materials, the nonverbal way in which the message is passed on or delivered. Thus, for robot assisted learning, the cloud environment of the r-Learning service framework should be considered. To establish the assessment criteria for robot assisted learning, it is reasonable to assume our HRI model (colored gray) based on the entire r-Learning framework shown in Fig. 1b (see also Fig. 5).

To be adopted and spread, new technologies need to have certain critical features, such as a relative advantage, compatibility, complexity, trial ability, and observability. The main idea of *the spread of new technology* can be attributed to Roger's innovation diffusion theory [30]. The technology acceptance model (TAM) included this belief-attitude-intention-behavior chain to the determinants behind IT acceptance and use [8].

Most previous studies have focused on new technologies such as computers or mobile phones. As the demand for robot-assisted learning has grown, the issue of robot acceptance has increased in importance. Previous studies have highlighted not only the user's cognitive appraisal of a new technology but also adoption theories that reflect engineering aspects. Hu et al. (2003) reported that a teacher's TAM was not related to consider job relevance when making initial acceptance decisions as well as after their use of technology [15]. It was argued that a teacher's TAM has a highly prominent and significant path, from job relevance to perceived usefulness, according to longitudinal surveys of 130 teachers. One study of TAM concentrated on a robot which was an Almere model of an assistive social agent for the elderly [14]. But it did not consider children in the learning and teaching environment. Moreover, robot-assisted learning has many features which differ from those of computer aided learning [12]. We consider two barriers preventing the spread of robots in learning and teaching environments except the psychological barriers of teachers: *a range of affordable robot kits*, including the price and repair costs, and *cloud services* from education authorities in Sect. 4.

3 Using robots in education for sustainable development

Most of the students being cared for at the child welfare centers in Korea are orphans, or are from single parents, grandparents, or even defector families from North Korea. According to social welfare officers involved in the present outreach program, it is estimated that approximately 50 % of the students who participated had learning disabilities or ADHD. The Korean government already supports various after-school programs for these children. Though robots may be tools to foster a student's self-efficacy in ESD, it is an enormous task to support a robot outreach program. The key problem pertains to how a robot outreach program can change students from low-income families over time. We provide a qualitatively analysis in Sect. 3.3 and a quantitative in Sect. 3.4.

3.1 Participants

For this study, eight facilities were randomly chosen from among the child welfare centers and the centers for North Korean defectors (the HANA Center) in Korea. The scale of seven of the centers was nearly identical (9–12 participants), but the largest center had fifty participants. In total, 131 students from eight centers participated in this outreach program, which lasted one year, alternating between six months with two types of robots. That is, for the first six months the seven centers adopted a CCA-type robot, and the largest center had a DCA-type robot. Then the centers exchanged robots for another six months. All of the participants in the outreach program thus experienced both types of robots. Eleven students dropped out in the second half of the program due to personal reasons, such as moves, hospitalizations, enrollments in after-school programs, and others. Table 1 shows the statistics of the 112 participants in the second half of the outreach program after the eight non-responsive students were excluded.

Table 1 Demographic statistics of participants

Item	Number of people
Gender	
Boy	97
Girl	15
Age	
8–9	24
10–11	55
12–15	33
Housemate	
Parent	33
Single father or mother	10
Relative	2
Protection facility (orphan)	50
Not regular	17

3.2 Robots and outreach program

Depending on their hardware configuration, the robots were divided into the *centralized controller architecture* (CCA) type and the *decentralized controller architecture* (DCA) type, as shown in Fig. 2. For the CCA-type robots, the connectors for the actuators and sensors needed to be individually connected to the controller in the manner of LEGO Mindstorm. This involved simple construction, but connections were only possible for a limited number of components. The robotic activities of the CCA type focused on creativity, problem solving, and self-portrayal through the robots. The DCA-type robots used a controller where modules were connected via daisy-chain cabling; a sub-processor was mounted on parts such as a motor or sensor to build the module. Given that a DCA-type robot can connect hundreds of various modules or more to one communication connector, complex multi-axis robots such as humanoid robots can easily be built. The robot activities of the DCA-type focused on reasoning skills and expressiveness.

As shown in Table 2(a), the instructors prepared occasional and weekly reports for the classes for which they are responsible. To improve the quality of education, each report was required to contain detailed descriptions of observations of individual students. Based on the instructor's reports, a project manager monitored how the class progressed. The instructors and the project manager produced semester and final reports together. The report system was organized into two stages for better education management. Moreover, issues pertaining to success/failure cases, performances, and improvements were shared through one joint workshop per semester and through occasional meetings.

Thirteen social officers of the child welfare centers, sixteen robot expert instructors, and sixteen undergraduate and some graduate volunteers who were majoring in robotics ran the program in two six-month programs. There were approximately ten students, one instructor, and two volunteers per class. Each program, as shown in Table 2(b), was

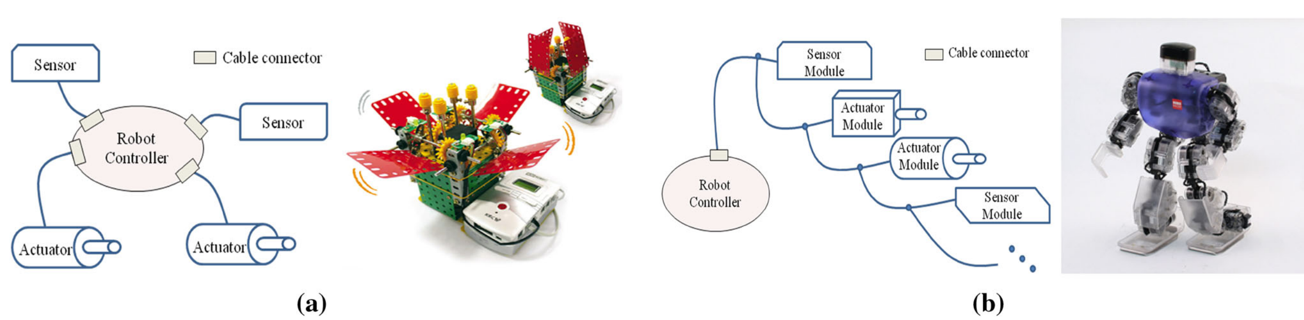
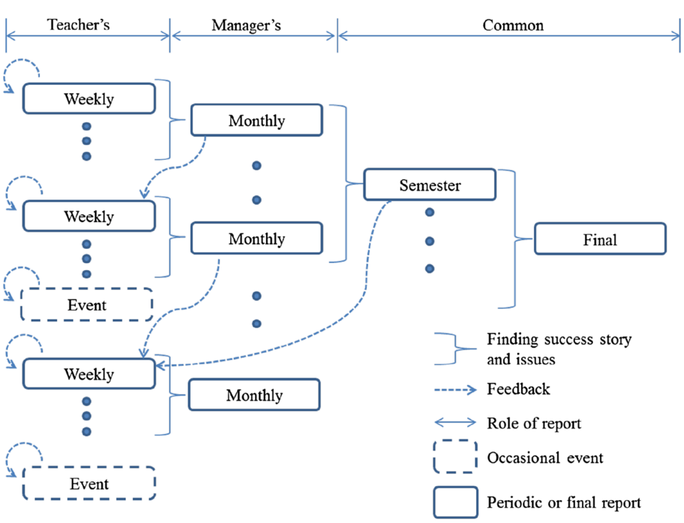


Fig. 2 The two types of robots used in the study. **a** CCA-type robot. **b** DCA-type robot

Table 2 Robot outreach program for sustainable development

(a) Class Management



(b) Weekly Curriculum

week	CCA-type robot class	DCA-type robot class
1	Introduction and setting	Introduction and setting
2	Car with an IR sensor	Joint setting and position control
3		
4	Moth with a CdS sensor	Door lock with one motor
5		Gripper with two motors
6	Flytrap with a Limit sensor	Car with four motors
7		Humanoid assemble
8	Doll with a Microphone	
9		Sample motion play
10	Automatic door with an IR sensor	Motion download
11		Programming tool instruction
12	Biped robot and link	
13	Insect programming	Hello motion
14	Planetary gear	Motion speed modification
15	Larva robot with a limit sensor	Push-up motion
16		Big bow motion
17	Bebel gear	Motion data combination
18	Sensor selection method	
19	Timing belt	Motion library manipulation
20	Line tracer with a DC motor and an IR sensor	
21		Robot dance

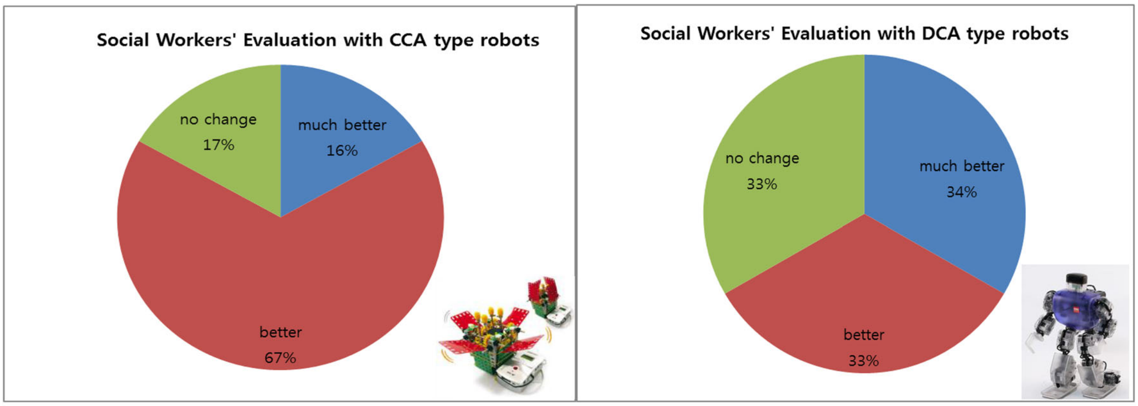
composed of regular classes at the centers, which were run for two hours/two times a week by the instructors, as well as a one-time session involving the demonstration of robot games operated by the volunteers.

The class was two segments 50 min long with a 10-min break, thus lasting for 2 h. For learning activities with the CCA-type robots, students talked about their dreams and hopes freely, to self-reflect, and to draw subject matter related to their dreams and hopes. An instructor guided students in imagining robots related to their subject matter and drawing the function and appearance of their imagined robots. The instructor then explained the robot parts and assembly instructions and supported each student as they designed and expressed their own robots in detail using these parts. The instructor let students discuss the robot parts that were prepared with great variety as well as their designs and let them exchange opinions about the robots. In an activity, students drew the problems that were solved by robots or solved them by themselves. An instructor encouraged each student to think creatively and to design naturally and differently while not offering straightforward solutions. The students were seriously devoted to their assembly tasks and continuously interacted verbally. The program encouraged students to reflect in various ways by comparing their robot assembly processes through presentations.

Secondly, to learn activities with DCA-type robots, the DCA-type humanoid robots were set to produce various basic motions (e.g., sitting, walking, turning around, hurrying). These were collected for motion programming (e.g., greeting, repeatedly sitting and standing, pushing up) and configured with work programming for any situation (moving three steps forward and sticking a flagpole). By programming motions and complex robot behaviors, the logical thinking of the students rather than creativity could be improved. During the final week, the instructor presented the most complex behavior scenarios in various situations for the students to discuss the programming. Students had to conceive of methods for solving the problems in the scenarios, such as obstacle avoidance, climbing stairs, and others.

3.3 Qualitative evaluation of behavioral changes

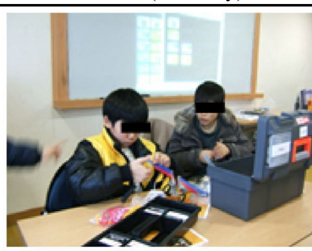
Given that our outreach program did not have a control group, we interviewed thirteen social officers who were staying with the students at the child welfare center. They qualitatively evaluated students' behavioral improvements with five-point Likert scales (much better, better, no change, worse, and much worse), as shown in Fig. 3. One non-response (7 %), due to the replacement of a social officer in the middle of the term, was excluded from the results. As shown in Fig. 3a, the students' behavioral changes with the CCA-type robot were as follows: 16.7 % of the students showed highly improved behavior, 66.7 % improved somewhat and 16.7 % remained the same. As shown in Fig. 3b, the behavioral changes of the students with the DCA-type robots led to similar percentages for highly improved, improved, and remaining the same. Because there were no reports of worse or much worse behavior for either type of robot, robotics education can be expected to be effective in improving the behavior of students.



(a) (b)

Fig. 3 Social officers' evaluations of changes in students' behaviors. **a** CCA-type robots. **b** DCA-type robots

Table 3 Some scenes of attitude changes over the six months of the course

ID	2nd week (February)	7th week (March)	21st week (June)
Y			
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Two individual success stories based on the accumulated weekly reports are shown in Table 3. For the CCA type, the representative success story was about student Y (a boy, 12 years old) who conducted himself negatively. In the early weeks, Y showed a considerably annoying attitude, saying that he could not understand how to make a robot at all. A picture from the seventh week showed that Y had created a helicopter by himself, though he did not complete the tail part of the helicopter. Instead, he decided to complete it during the next class. In the last week, Y made a smiling robot that performed acrobatics in combination with a seesaw. Y finished sooner than the other students and therefore had time to decorate the robot. Y thus developed the habit of finishing what he set out to do. Secondly, the representative successful case with the DCA-type robot involved student C (a boy, 10 years old). In the early weeks, C refused to participate in the robot class and ran around inattentively with other kids, spoiling the class. The instructor was so bothered by this that she preferred his absence from the class. In the 7th week, although C still chatted too much during the class, he was gaining a competitive mind. C began to show growing interest in robots, trying to make other motions by himself. He started to nag his instructor to help him when his robot did not move as well as others' robots. During the 21st week, C did not chat anymore and became immersed in the programming of the robot's motion. Although he was irritated when his programming did not work well, C participated very well in general.

The following reports are from interviews with two social officers.

A: "I am supporting the operation of many education classes for students with ADHD or from low-income families in my center. These students show problematic behaviors even after they go on to middle school. When I was involved in other programs, it was very difficult to make the children concentrate on the program. Frankly speaking, I was very skeptical about robot education at the beginning, like the other programs. Therefore, when the program was advertised to students, I strongly urged the exclusion of any ADHD student. However, the project manager from a university said, "I understand. Please give them a chance to take part. To help you and the instructors, undergraduate or graduate students majoring in robots will be there as volunteer teaching assistants." Thus, I agreed to include students with ADHD. Actually, it was so amazing to see how distracted children gradually changed to pay attention in the class. It was very hopeful to see these children able to concentrate and participate in the programs with their friends."

B: "In the robot class, individual differences are somewhat severe because the intelligence and behavioral problem levels are diverse, but it was touching to see the opportunity given to students to discover their talents. Most children in this center have never had learning opportunities involving robotics because of money and/or unconcerned parents. In a special lecture, the professor told the children that someone with the highest achievement in the robot contests could enter the robot department of his university in the future. I am sure there were several talented children at this center who could achieve this. If they were born into an ordinary family, they would not have missed such an opportunity. The children in my center would have missed it if this program had not been supported. I feel very sorry for ending this program in only one year. I hope the program will be continued in the future. Specifically, talented children should be provided with the opportunity to continue their learning in the second and third years, not limiting them to a one-time participation."

3.4 Quantitative analysis for mental health

In this section, the effects of robot education targeting low-income children during a year, involving aspects of changes in mental health areas (immersion experience, ego-resiliency, depression, discouragement, aggression) were analyzed quantitatively, similar to the method in Choi et al. [7]. Because it is uncertain whether robot education was the only effect that influenced the participants during the year (a long time) in which the program was run, a set of control group data was created by selecting 30 students who were in the same environment, but did not participate in the robot education, and surveying them with the same questions. A pre-test was conducted in the form of a self-answered survey during the first week, and the aspects of change were measured by conducting a post-test during the final week of the session year. For this assessment, we chose the tool used in Jung et al. (2008) [17]. We randomly selected an experimental group (50 students out of 119 students) and a control group (50 students) who had had no experience of robot education, and then compared the pre and post-test for the two groups as shown in Table 4. The child psychologist said that the results of the comparison could not be treated as significant because of the uncertainties involved in child mental health area and the experiment period (a year).

It was found that the effects of the immersion experience and ego-resiliency were significant at $\alpha = 0.1$ in the mental health areas. It can be said that students who received robot education enhanced their levels of immersion and/or ego-resiliency, helping them improve their capacity to overcome difficulties. However, because there were no significant differences in other factors (depression, discouragement, aggression), it can be interpreted that there are no side effects of robot education. In other words, it was shown that students' positive capabilities improved at the same time there were no side effects, such as an increase in negative features, as a result of the robot education. The following graphs show this (Table 4 and Fig. 4).

4 TAM for robots on cloud platform

4.1 Robot service acceptance model

As an emerging technology, robots presently have a relatively slow adoption trend, as they are not yet cost-competitive for many applications. However, there is an opening of new opportunities for robots in the education sector. Unlike devices such as computers, lap-tops, and smartphones, anthropomorphized robots can produce numerous nonverbal messages with their facial expressions, arms, and legs. Additionally, robots can adopt their voice engine-TTS (Text to Sound)- with various pitches as para-verbal messages. Thus traditional TAM may not be reasonable for robots that have the types of external factors discussed here, as mentioned in Sect. 2.2, because it considers the inner factors of users of new technology.

Cloud computing is becoming an attractive technology in the teaching and learning environments discussed above. MOODLE (Modular Object-Oriented Dynamic Learning Environment), a free online learning management system, provides students access to others who may be located far away, in a massive, open, and connected setting. Most cloud computing studies that are focused on learning consist of topics such as technology for the future long-distance education cloud, teaching information systems, the integration of teach-

Table 4 Comparison of changes in mental health areas

Group	Standard variable		Mean	Standard deviation	t-value	Degrees of freedom	p-value
Experimental group	Immersion experience	Pre-test	7.90	1.85	(1.66)	49.00	0.10*
		Post-test	8.56	2.41			
	Ego-resiliency	Pre-test	7.85	1.86	(1.82)	47.00	0.08*
		Post-test	8.52	2.18			
	Depression	Pre-test	6.67	2.09	0.71	48.00	0.48
		Post-test	6.35	2.78			
	Discouragement	Pre-test	6.77	1.43	0.36	47.00	0.72
		Post-test	6.67	1.85			
	Aggression	Pre-test	6.50	2.02	(0.14)	47.00	0.89
		Post-test	6.56	2.78			
Control group	Immersion experience	Pre-test	8.47	2.42	(0.68)	29.00	0.50
		Post-test	8.77	2.03			
	Ego-resiliency	Pre-test	8.70	2.26	(0.18)	29.00	0.86
		Post-test	8.77	2.01			
	Depression	Pre-test	6.48	2.53	0.10	28.00	0.92
		Post-test	6.41	2.81			
	Discouragement	Pre-test	6.93	1.70	0.95	29.00	0.35
		Post-test	6.53	1.80			
	Aggression	Pre-test	6.79	2.44	(0.30)	28.00	0.77
		Post-test	6.97	2.67			

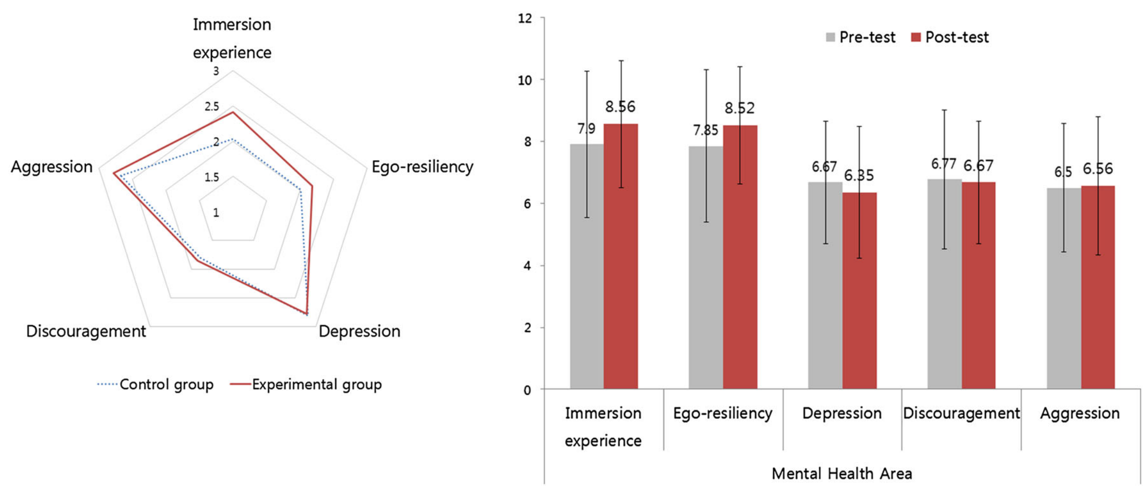

Fig. 4 Comparison of mental health areas

ing resources, and teaching systems development [23]. Mitra (2013) prepared for future learning using Self-Organized Learning Environments (SOLE) and by connecting them with a global team of volunteer mediators known as Grannies [27,38]. MOOC (Massive Open Online Courses) for higher education [21] may be extended and shared by robotics educators in MOODLE to overcome the lack of ready-for-use lesson materials.

The HRI model in a cloud environment consists of ① the *robot*, ② the *message* (verbal, para-verbal, non-verbal), ③ the learning/teaching *cloud environment*, and the *human receiver*, as mentioned in Sect. 2.2. We have proposed a technology acceptance model, designated a RSAM (Robot Service Acceptance Model) based HRI model in a cloud environment, as shown in (b) of Fig. 1. The three components of RSAM shown in Fig. 5 are the important criteria factors for teachers (or educational public officials) who seek to adopt robot assisted learning in schools.

Using a pilot interview with seven teachers who are involved in robot-assisted learning, we determined the pri-

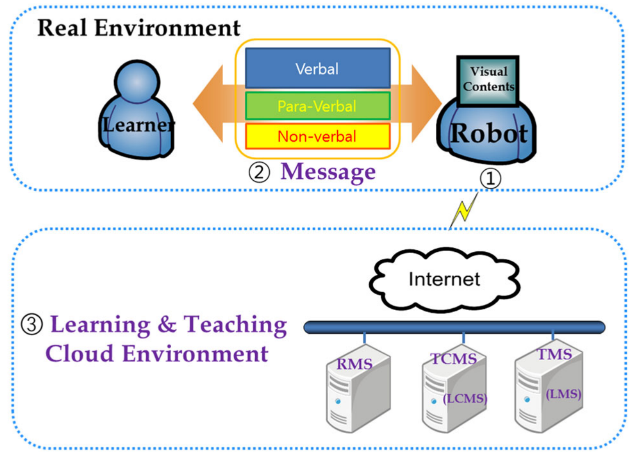

Fig. 5 RSAM model, which is similar to the gray area in (b) of Fig. 1

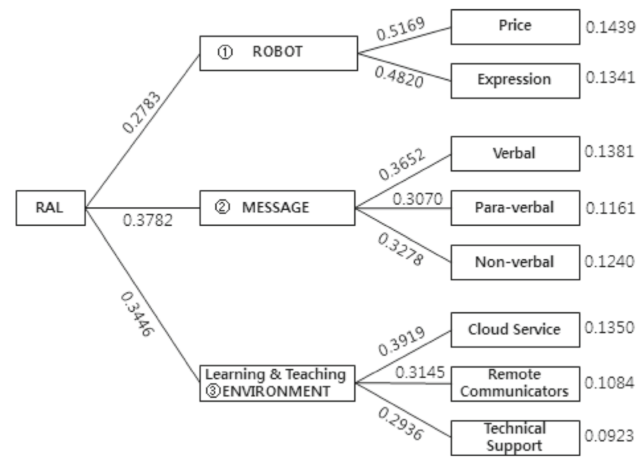

Fig. 6 Estimated weighted values of RSAM

mary sub-factors of three components, as follows (see also Fig. 2). For ① the *robot*, these are *price-competitiveness* and the ability of the hardware to express the robot characteristics well. The price of a robot is in inverse proportion to *the expressiveness of the robot body*: expressiveness is simple if the price is low, and the robot will have a hardware body that can express many concepts if the price is high. For ② this *message*, the robot act of communication involves *verbal, nonverbal, and para-verbal components* similar to the human communication model of the law of Mehrabian. For ③ the *cloud platform*, *cloud service* for learning/teaching activities, *remote communicators* for tele-operated robots (or teachers for autonomous robots) and *technical support* are prerequisites for a learning and teaching environment. Specifically, technical support including repairs, training and advice, as would be provided to customers (teachers) by certain robot providers, is a basic requirement for the adoption of robots in schools.

We discriminated the relative importance of these factors using a survey with a focus group to collect the views of users of RSAM, i.e., teachers, in the next section.

4.2 Estimating the relative importance of RSAM

RSAM, which uses a decision tree for robot-assisted learning, is shown in Fig. 6. To estimate the weight values between the RSAM factors, five surveyors received an orientation session for face-to-face interviews and were trained. A three-minute video of simulated robot-assisted learning was filmed before the survey. The interviewee gave weights to each of three factors (robot, messages, learning and teaching environment) on a scale of 1–100 for the question 'How important do you think these factors are to adopting robot assisted learning in school?'. The sum total in the first depth of the decision tree must be 100 %. Then the sub-factors in the second depth were weighted to allow an amount of 100 % in all.

The survey was carried out with 270 elementary teachers in five face-to-face sessions. Three data instances were eliminated because the sub-factors of RSAM did not add up to 100 %. Figure 6 shows the weighted values of the relative importance assigned by teachers for adopting robots in a teaching and learning environment. The relative ratios of the first depth for robot-assisted learning are 27.8 % for *robots*, 37.8 % for *messages*, and 34.5 % for the *environment*. Teachers felt that the robot (verbal, nonverbal and para-verbal) message in class was slightly more important, as they focused on the activities of the robots in their classes.

In the second depth for the factor *robot*, *price* (51.7 %) was a more important sub-factor than *expression* (48.2 %). For the factor, *message*, teachers expected that the *verbal* message was most important with a relative importance proportion of 36.5 %. They considered para-verbal at 30.7 % and non-verbal at 32.8 % quite different from the law of Mehrabian as cited in Sect. 2.2. For the factor *teaching and learning environment*, they expressed the need for a *cloud* environment at a rate of 39.2 %.

The highest total weighted proportion among eight sub-factors was *the price* of the robot, which came in first at 14.4 % (=0.2783×0.5169), followed by the *verbal* message at 13.8 %. They considered *the price* of the robot to be the most important issue preventing the use of robots in schools. *Cloud services* and *expressions* came next.

5 Conclusions and discussion

The first contribution of this paper is the examination of the long-term potential of robot education for children from low-income families, quantitatively as well as qualitatively. While the usefulness of robot education has been studied many times, the number of studies focusing on ESD is relatively low. There are no studies comparing the effect of outreach robot education on behavior changes and mental health areas.

It was qualitatively and quantitatively observed that students from low-income families with low self-efficacy and learning disabilities can improve through robotics education in the long-term. In this study, effective education methods and observations were presented and shared through individual learning activity reports, which were prepared with instructors, social officers, volunteer students as teaching assistants, and a project manager every month. The social officers and instructors identified success stories in which students' self-efficacy levels and learning attitudes improved.

In addition, we compared the differences of two types of robot used in the outreach education. Specifically, the social officers found that DCA-type humanoid robots resulted in more positive effects than CDA-type robots. Therefore, it can be assumed that intelligent robots (the DCA-type humanoid robots) are somewhat more effective than a creative type of assembly robot in achieving positive student outcomes.

In the results of surveys on long-term changes in mental health areas, based on comparisons of pre- and post-tests of participants and a control group, it was found that the level of immersion and ego-resiliency factors were increased through robot education. Therefore, according to the results of a qualitative analysis based on social officers' judgments, and the quantitative analyses, it can be said that both show positive results.

Further studies which compare CDA-type and DCA-type robots by groups could expand the analysis in various important areas (capability of effectiveness and self-understanding, feelings of happiness, social capability-interpersonal relationships, family relationships, intellectual capacity-math intelligence, and linguistic intelligence) and thus should be carried out in the future.

Along the current trends of MOODLE, the r-Learning service framework comes in near future. This condition requires the development of assessment criteria to evaluate robot assisted learning.

In that regard, the second contribution of this paper is in defining an HRI model and a technology acceptance model for robots, RSAM, as assessment criteria within the r-Learning service framework. While the effectiveness of this type of robot education is being studied in diverse ways, there is no study of TAMs which involve robot-assisted learning in schools. There are several studies of TAMs involving assistive social robots, but they focus on psychological factors such as the attitudes and enjoyment of elderly users, and not children.

In addition, some previous works on criteria for robot assisted learning have concentrated on the robot based message and did not consider the robot as a sender (or receiver). Since the knowledge of the robot is distributed in a cloud environment, we suggested a RSAM based on a cloud platform and a HRI model for robot-assisted learning. The RSAM was used to estimate the relative importance of factors affecting teachers who may adopt robots in teaching and learning environments, using focus group interviews. It was determined in the RSAM that robot providers should consider the most important factor to be *the price* of the robot, followed by the *verbal message* that the robot delivers and the *cloud platform* and *expressions*when constructing a robot service framework for use in teaching and learning environments.

Given the challenges faced by proponents of robot-assisted learning, especially considering cloud services, we can suggest that tele-operated robots will become leaders in the area of robot-assisted learning given the dominant factors in the RSAM. Tele-operated robots are less expensive than autonomous robots and can easily deliver their own *verbal* and *non-verbal* messages via the internet. Further studies are needed for a practical assessment of tele-operated robots in robot-assisted learning.

Acknowledgments This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (NRF-2012R1A1A2039797l; 2015R1D1A1A09060450) and partially by a research grant from Kwangwoon University in 2016. Figure 3 was shown in the paper 'Success Stories of Children from Low-income Families in Robot Education' from the proceedings of International Conference on Convergence Technology, p866-867, June 29-July 2, Hokkaido, Japan, 2015

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