FACTORS INFLUENCING LEARNING OF COMPUTATIONAL THINKING SKILLS IN YOUNG CHILDREN

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Abstract

Objectives or purposes

There is increasing recognition of the importance of computer science education for young children. Computational thinking (CT) skills are the cognitive processes involved in solving problems with computers and other technologies. It is vital that all students, regardless of their background, have an equal opportunity to acquire CT skills. However, little is known about the factors that influence learning and development of this important skill set. This paper explores how demographic and environmental factors relate to students' acquisition of CT skills.

Methods

Nearly 600 1st and 2nd grade students from the Norfolk, Virginia school system completed a six-week *Coding as Literacy* (CAL) coding curriculum that included 12-14 hours of instruction with the KIBO educational robotics platform.

Data Sources

Students received the *TechCheck* assessment (Relkin, et al., 2020) before, during, and after the CAL curriculum. *TechCheck* is an "unplugged" CT assessment that is developmentally appropriate for children ages 5-9. "Unplugged" refers to the use of challenges that are analogous to those that arise in the course of computer programming that do not require knowledge of computer programming to be solved. Students were asked to share their self-identified gender. Other background and classroom information were collected from the schools with parental consent. Teachers were administered the TACTIC-KIBO coding and CT assessment after completing a professional development workshop.

Results

Students in first and second grade (N = 573, ages 5-9, M_{age} = 7.22) from 8 schools and N=35 first and second grade educators participated in this research. 302 students identified as female, n=261 students identified as male, n = 10 did not specify a gender. The majority of students identified as Black/African American followed by White, Bi/ Multiracial, Hispanic/Latino/a, Asian/Pacific Islander, and Native American. We used regression analysis to explore how children's performance on *TechCheck* related to their gender, grade, age, race, school, and teacher. We found that teacher and school contributed significantly to the regression model. Grade, age, gender and race/ethnicity were not significant predictors of changes in CT scores. Multilevel modeling revealed that teachers' scores on a coding/CT assessment (TACTIC-KIBO) predicted student CT learning.

Significance

We examined how students from a variety of demographic and environmental backgrounds performed on an unplugged CT assessment while participating in a coding curriculum designed to promote literacy and CT skills. The findings that teachers and schools are significant predictors of CT learning can potentially inform the design of better computer science curricula, professional development courses for teachers and CT teaching tools for young children.

Introduction

Computational thinking (CT) skills are cognitive processes typically exercised in coding (computer programming) that are also applicable to many other disciplines. It is vital that all students, regardless of their background, have an equal opportunity to acquire CT skills. However, little is known about the factors that influence learning and development of this important skill set in young children. The current investigation is part of a larger study called the Coding as Another Language - KIBO robot (CAL-KIBO) project. The main goal of the CAL-KIBO project is to explore the impact of an integrated coding and literacy curriculum on young children's acquisition of coding, CT, and literacy skills. This paper explores how demographic and environmental factors, including teaching experience, relate to students' acquisition of CT.

There has been increasing interest in CT as demonstrated by the abundance of publications on CT educational interventions and evaluations, domain definitions, and assessments (Chen, et al., 2017; Lye & Koh, 2014; Tang, et al., 2020; Zhang & Nouri, 2019). Wing, 2006 suggested that CT skills are not only beneficial in computer science but also in many other fields. However, women and certain minority groups are under-represented among those who pursue a degree in Computer Science (National Center for Women and Informational Technology, 2020; Google & Gallup, 2016). Females are reportedly more likely to develop technology phobias which can, in theory, impact on acquisition of CT skills (Özyurt & Özyurt, 2015; Sullivan & Bers, 2016; Cheng, 2019). Access to technology may vary as a function of race, socio-economic status and other factors (Google & Gallup, 2016). A 2021 international study found that students from lower SES have lower level CT skills on a task-based assessment than those from economically advantaged backgrounds (Karpiński, et al., 2021). Little is currently known about whether and how these and other factors influence the acquisition of CT skills in young children.

Since the importance of CT in education has been recognized, there has been a parallel increase in CT professional development programs for teachers (Fraillon, et al., 2018; Tang, et al., 2020). However, the impact of teaching experience on students' acquisition of CT has not been extensively studied. Nouri et al., (2019) interviewed teachers who had been implementing coding in their classrooms for 1-4 years and found that many were not familiar with basic coding/CT concepts. Past studies indicate that teachers' skill level and competence in teaching CT can limit the CT skills that their students will acquire (Whittle, et al., 2015; Saidin et al., 2021). Since teachers vary in their experience as well as familiarity with technology and CS concepts, it is important to explore how these factors may affect CT education. This information can help in the creation of better teaching programs and professional development initiatives (Nouri, et al., 2020; Relkin et al., In Press).

Recently, the CAL- KIBO curriculum was created to connect powerful ideas of programming to parallel concepts in natural language and literacy in a way that is developmentally appropriate for children 5-9 years of age. The first version of this curriculum used the children's book *Where the Wild Things Are* by Maurice Sendak and the KIBO robotics platform as its foundation. A quasi-experimental longitudinal study carried out in multiple schools in a Virginia school district found that the CAL-KIBO curriculum significantly improved coding and CT skills in young children (Relkin et al., 2020; Hassenfeld et al., 2020; Relkin et al., in press). As part of this study, participating teachers completed surveys about their teaching experience and CS background and took an assessment specific to the KIBO robotics platform that evaluates coding/ CT skills (TACTIC-KIBO (Relkin, 2018; Relkin & Bers, 2019)). Participating students were administered an unplugged CT skills assessment (*TechCheck* (Relkin et al., 2020)). Using this data, we sought to answer the following questions:

1. Do demographic and environmental factors such as gender, grade, age, race, school, and teacher predict young children's acquisition of CT skills in association with the CAL-KIBO coding curriculum?
2. Do teachers' experience and CT skill level predict students' acquisition of CT skills through the CAL-KIBO project?

Methods

Participants

Participants were 1st and 2nd grade students and their teachers from an urban school district in Norfolk, Virginia. Students were from diverse racial/ethnic and socio-economic backgrounds. All schools had a high number of military-connected and low-income students. Eight schools were invited to participate under a US DoDEA grant (WORLDCL10). We originally recruited 1138 child participants from eight different schools as well as 30 first grade and 27 second grade teachers. The subset of participants included in this analysis were neurotypical students (N = 573) who completed two time points of *TechCheck* (baseline, end point) and end point *TACTIC-KIBO*. Teachers (N = 35) of those students who had completed a pre-survey and the TACTIC-KIBO assessment were also selected. The study was carried out with opt-out parent/guardian informed consent, child assent and written consent from all participating teachers. Demographic information on students was received from the participating schools and was anonymized in compliance with an IRB-approved protocol.

Measures

The following measures were used to assess participants coding and CT skills:
***TACTIC-KIBO* (platform-specific coding and CT assessment)** This instrument classifies CT abilities into seven domains and four proficiency levels. It is designed for children between 5-9 years of age with some knowledge of the KIBO coding platform. The questions in *TACTIC-KIBO* are based upon Bers' (2018) developmentally appropriate theoretical framework of seven powerful ideas of computer science. The domains assessed are Algorithms, Modularity, Hardware/Software, Control Structures, Debugging, Representation, and Design Process. Each correct answer is given 1 point. Total score is the sum of all correct answers. Scores ranged from 0-28 with higher scores indicating more correct answers. *TACTIC-KIBO* was a summative assessment given to teachers at one time point after the professional development training for teachers.

***TechCheck* (unplugged CT assessment)** *TechCheck* is a 15-item multiple-choice assessment that uses unplugged activities to probe six domains of CT. Unplugged activities consist of puzzles, games and other exercises that exemplify CS principles without requiring the use of computers or other technologies. The domains assessed by *TechCheck* are Algorithms, Modularity, Hardware/Software, Control Structures, Debugging, and Representation. Scores range from 0-15 with higher scores indicating more correct answers. *TechCheck* change scores were calculated by subtracting the students' baseline score from the endpoint score.

Procedure

Teachers attended a one day, in-person professional development training led by researchers at the start of the study. In addition to learning about the foundations of KIBO and the CAL-KIBO curriculum, teachers engaged in hands-on play with the KIBO robot by participating in various activities from the curriculum. Researchers assisted in teacher planning and practice so that they could effectively integrate the curriculum into their classrooms. At the end of the training all consenting teachers were asked to complete a survey and to take the TACTIC-KIBO coding/CT assessment. The pre-survey collected demographic data as well as information about prior teaching and coding experience. After the professional development program, the teachers were given two weeks to prepare their coding curriculum lesson plan. Throughout the curriculum, coaching was given to educators through phone calls with researchers and in-person assistance from administrators and technology specialists. One week prior to initiating the curriculum, the *TechCheck* assessment was administered to their students by one of eight (one per school) Instructional Technology Resource Teacher (ITRT) proctors. ITRTs were trained to administer the *TechCheck* and TACTIC-KIBO assessments in a consistent manner. The last *TechCheck* assessments were given to students after the full curriculum had been completed. The TACTIC-KIBO assessment was administered a single time to students within a week of the final *TechCheck* assessment.

Analysis Plan

Statistical analyses were conducted in R (Version 3.6.1, R Core Team, 2019) using R Studio version 1.2 and IBM SPSS (Version 26, 2019). Screening analyses were performed to investigate normality, linearity, and outliers. Pearson correlation coefficients were calculated to examine the bivariate relationship between all variables. A simultaneous regression was carried out to examine whether the change in *TechCheck* (unplugged CT assessment) score from before the CAL-KIBO curriculum to after was predicted by students' gender, grade, age, race, school, and teacher.

To address the relationship between student outcomes and teacher experience, a multilevel linear mixed model was conducted using the "lme4" package (Bates, et al., 2015) and the "lmerTest" package (Kuznetsova, et al., 2017). The clustering unit was the classroom (teacher) and predictors were teacher TACTIC-KIBO score, student grade, and years of teacher experience. The level one predictor was student grade. The level two predictors were teacher TACTIC-KIBO score and years of teacher experience. The outcome variable was student *TechCheck* change scores. Maximum Likelihood (ML) was used because there were over 30 nested groups (classrooms) and because the models differed in their fixed effects (Snijders & Bosker, 2012). Likelihood ratio tests were used to assess the impact of adding additional predictors to a null model.

Results

Students in first and second grade (N = 573, ages 5-9, M_{age}= 7.22) from 8 schools and N=35 first and second grade teachers were included in this analysis. There were slightly more female (n= 302) than male students (n=261) and n=10 students chose not to specify a gender. The largest single racial/ethnic group of students were identified as Black/African American followed in order of prevalence by White, Hispanic, Bi/Multiracial, Asian/Pacific Islander, and Native American.

Thirty-five teachers were included in this analysis. All teachers were female. Their ages were not collected in this study. The majority of teachers reported that they were White, followed in frequency by Black/African American. 60% of teachers reported that they had "a little" prior coding experience, 37.44% said that they had never coded before. Only 1 educator reported substantial experience with coding. None of the teachers had prior experience with the KIBO robot. The educators had substantial teaching experience with the majority teaching for more than 5 years. 22.85% had 0-5 years experience, 28.57% had 6-10 years, 8.57% taught for 11-15 years and 40% had 15 or more years of experience (See table 1). After a training course with the KIBO robot, teachers completed the 28 item TACTIC-KIBO assessment of coding and computational thinking. Examination of Z scores for this measure revealed no extreme outliers.

Table 1

Student/Teacher Demographics and Survey Results

STUDENTS	Total N =	573	**TEACHERS****	Total N =	35
Self- reported age	Mean	7.22	**Self- reported coding experience**	Never	13
	SD	0.78		A little	21
	Range	5-9		A lot	1
Self- reported gender	Girl	302	**Self- reported teaching experience**	0-5 years	8
	Boy	261		6-10 years	10
	Rather Not Say	10		11-15 years	3
				15+ years	14
Race/ethnicity*	Black/African American	243	**Race/ethnicity**	Black/African American	9
	Hispanic or Latino/a	67		Hispanic or Latino/a	1
	Bi/ Multiracial	52		Asian or Pacific Islander	1
	Asian or Pacific Islander	20		White	21
	White	225		Not Specified	3
	Native American	5			

* Race/Ethnicity are not mutually exclusive for students
** Self-reported gender was 100% female for teachers

We used regression analysis to examine the variables that predicted the *TechCheck* change score (post – pre curriculum). Independent variables included gender, grade, age, race, school, and teacher. We found on step-wise linear regression that teacher ($\beta = -.13$) and school ($\beta = 0.01$) were significant predictors of the *TechCheck* change score $F(2, 570) = 9.17$, $p < .001$. Grade, age, gender, and race/ethnicity made only minor contributions to the variance in this model and were not found to be significant predictors.

We administered the TACTIC-KIBO assessment to teachers after they completed the professional development program as a rough measure of their facility with the KIBO robotics coding platform. Although most teachers (22/35) were rated as "fluent programmers" based on their TACTIC-KIBO scores, 11 teachers performed at the intermediate "programmer level" and 2 were rated as "early programmers" which is considered a novice level. This range of performance was not entirely unexpected since the majority of participating teachers were being introduced to coding and the KIBO robot for the first time in the pre-study professional development workshop.

To better understand the factors that may contribute to teachers' influence on the *TechCheck* change scores of their students, we performed a multilevel model that incorporated teachers' self-reported teaching experience, coding experience, and post professional development TACTIC-KIBO scores. The model of *TechCheck* change scores with the best fit contained the fixed effects of teacher TACTIC-KIBO score, teacher self-reported coding experience, and years of teacher experience with the random effect of classroom (intercept). When grade level was added, the model fit did not significantly improve $\chi^2(1) = 0.00$, $p > .05$. We conducted a likelihood ratio test between the null model with *TechCheck* change score as the outcome and a model with the predictors of teacher TACTIC-KIBO score and years of teacher experience with the classroom as a random effect. The model significantly decreased deviance $\chi^2(2) = 1205.90$, $p < .01$ indicating that the model with those predictors was a better fit than the null model. The only significant coefficient was the teacher TACTIC-KIBO score which was significant at the $p<.05$ level. Notably, coefficients for years of teaching experience and self-reported teacher coding experience did not reach significance in this model ($p>.05$). Post- hoc analysis of residuals for the model showed a random distribution of residuals around zero with no asymmetries or trends that would otherwise suggest fitting error.

Discussion

In this study, we investigated predictors of CT learning following the CAL-KIBO coding curriculum. Regression analysis indicated that the student's teacher and the school they attended significantly predicted response to the curriculum whereas age, grade, gender, and race/ethnicity did not. Multi-level modeling suggested that teachers' coding and CT skills as measured by TACTIC-KIBO after a PD program were significantly associated with changes in their student' CT performance following the CAL-KIBO curriculum.

Our findings support the notion that teachers who achieve competency in coding and familiarity with CT concepts are better prepared to promote the development of CT in their students. This speaks to the importance of good professional development for promoting CS education including teacher assessment to confirm that teachers have mastered the concepts that they will be conveying.

The educators' years of teaching experience was not found to be a significant predictor of the CT learning in the current study. This may be the result of two opposing effects. On one hand, more experienced teachers tend to be older and may have grown up with less exposure to technology, robots and coding than their younger counterparts. On the other hand, more experienced educators might be more effective in conveying the concepts embodied in the coding curriculum. It is conceivable that these two opposing influences effectively cancelled one another out, causing teaching experience not to be a significant predictor of the outcome. Future studies should more carefully measure teachers' past exposure to technology and coding to better account for these variables in a multilevel model. Other possible explanations for the lack of significance include under-representation of some ranges of teacher experience in this data set and a high degree of variance in outcomes within the teacher experience groups.

Teachers' self-reported coding experience did not significantly correlate with teachers' TACTIC-KIBO scores (r=.13, p >.05). This lack of correlation may be due to the fact that the majority of teachers had little or no past exposure to coding. In contrast, their TACTIC-KIBO scores reflect what they learned about coding KIBO in the professional development program.

School was found to be a significant predictor of CT learning in the regression analysis. There is some evidence that the fidelity of implementation of the curriculum varied across schools. For example, the number of KIBO robots available per student tended to be consistent within a school but varied between schools. Factors such as time allotted to teaching the lessons and protocol-permitted modifications to the curriculum also introduced between school variance. Future studies should control for the effects of these factors.

In initial examinations of data from this study, modest effects of gender, age, and race/ethnicity were detected in the baseline *TechCheck* scores. The current analysis, which focused on changes in association with the CAL-KIBO curriculum, did not find evidence that these variables were significant predictors of the outcome. Exploratory modeling with interaction terms for these variables also failed to show a significant contribution to the overall variance. While previous literature suggested that these variables can be relevant to the acquisition of CT skills by young children (National Center for Women and Informational Technology, 2020; Google & Gallup, 2016; Mioduser et al., 2009), the current study design and data did not confirm an effect.

Limitations

The current analysis employed data from a quasi-experimental study that was not specifically designed to measure the factors that predict CT learning. The parent study was not powered to examine the effects of all the variables of interest. In addition, we only had the opportunity to study two grades which provided a limited distribution of student ages. Our initial intention was to administer the assessments to Kindergarten students as well as first and second graders. Although Kindergarten teachers attended professional development and took the

TACTIC-KIBO assessment, we were unable to implement the Kindergarten CAL-KIBO curriculum due to school closure from the COVID-19 pandemic.

Another limitation was that there was sparseness in the data for some of the groupings. For example, only 8.57% of teachers had 11-15 years of experience. Only 1 teacher had extensive past coding experience. There was not equal representation of all races/ethnicities among students and teachers. The data sparseness may have limited our capacity to discern the effects of the predicter variables.

Years of teaching is not a comprehensive measure of teacher experience. Likewise, TACTIC- KIBO was not designed for assessing CT and coding ability in adult teachers. Additional information about educators' experience teaching STEM subjects and providing coding instruction might be more salient to the goals of this study. Inclusion of measures of fidelity of implementation of the curriculum might also permit better prediction of student CT learning outcomes relative to the teaching variables that were modelled in this analysis.

We did not take into account other potential factors that could influence children's CT score. For example, we did not have enough students with disabilities to examine whether neurodiversity affects student score. In addition, we did not take into account socio-economic status. Future studies will examine these variables.

Significance

In this study we examined demographic and environmental factors that may predict students' performance on an unplugged CT assessment following participation in a coding curriculum (CAL-KIBO) designed to promote literacy and CT skills. The findings that teacher and school are significant predictors of CT learning speaks to the importance of professional development courses for teachers and institutional commitment to teaching coding and CT to young children. Other factors such as curricular content and implementation can affect the acquisition of CT skills (Relkin et al., In Press; Arfe et al., 2019). Additional studies are needed to identify best practices to enhance the development of CT in young children.

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