A Generalized Estimating Equations Approach to Investigate Predictors of Teacher Candidates' Views of Coding

Predictors of View of Coding

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We use a generalized estimating equations approach to investigate predictors of preservice, early childhood teachers' views of (a) nature of coding, (b) integration of coding into preschool classrooms, and (c) relation of coding to fields other than computer science (CS). Predictors entered into the model were study, time point (pre-survey versus post-survey), prior programming knowledge and experience, ten latent survey factors, and the inclusion of lesson design/field experience. Significant predictors varied according to the specific view of coding being predicted. Views of the nature of coding were predicted by time, prior robot programming experience, perceptions of the value of coding, and intermediate programming knowledge. Views of the integration of coding in preschool were predicted by time, and perceptions of mathematics. Views of the relation of coding to non-CS fields were predicted by time and perceptions of the value of coding.

CCS CONCEPTS • Applied computing: Education

Additional Keywords and Phrases: early childhood education, motivation, prediction, teacher education, views of coding

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1 INTRODUCTION

Including coding and robots in the ECE curriculum is meant to invite all children to consider computer science (CS) pathways, and learn important skills for an information intensive future. But it is one thing to call for the inclusion of robotics and coding in ECE classrooms, and another thing to actually achieve it. To successfully integrate robotics and coding in ECE classrooms requires that ECE teachers have the tools (i.e., skills and resources) and motivation to do so. Little is known about the relative influence of the possession of the tools and motivation to integrate robotics and coding in ECE contexts on views of the relevance of coding to ECE. That is the gap that this study fills. Studying preservice ECE teachers from five studies on integrating robotics and coding in ECE, we used data on motivation, prior experience, and studies to predict the views of (a) nature of coding, (b) how coding can be integrated into preschool classrooms, and (c) how coding relates to fields other than CS, and to examine how such views change from pre- to post-survey.

2 LITERATURE REVIEW

2.1 Early Childhood Education

Within the USA, early childhood education (ECE) is typically defined as education for children from birth to age 8, and is divided into infant/toddler, preschool, kindergarten, and early elementary. Within ECE, there is a strong focus on children learning cognitive and socio-emotional content and skills through play, especially in infant/toddler and preschool settings [1], [2]. Preschool serves children aged 3-5, and focuses on socio-emotional development, preliteracy skills, mathematics skills. Kindergarten is the first formal schooling some children receive, and is seen as a bridge to formal schooling. As children move into kindergarten and early elementary levels, a partial shift away from play and toward more structured classroom interactions occurs [3].

2.1.1 Coding and Robots in Early Childhood Education

To help children learn important skills for the information age, and to consider CS pathways, the use of coding and robots is often encouraged in ECE [4]. Such skills include the abilities to decompose and address problems using algorithmic thinking, defined as understanding and addressing problems through the creation, interpretation, and use of replicable problem solving processes incorporating such CS processes as repeat while loops [5], [6]. CS is rapidly growing and lucrative, but undoubtedly not all children will become computer scientists, nor should they. Learning algorithmic thinking can help children build towards CS pathways, but also solve diverse problems.

Consistent with the focus on play in ECE, especially at the preschool and kindergarten levels, teaching coding is often couched within play [7], [8] and dance [9], [10] in ECE settings. This can be done through the use of robots [8], [9] and storytelling [7]. For example, ECE learners can include robots as partners in dramatic play. To do so, they need to choreograph moves and instruct the robot to perform such moves using coding. This often requires that ECE learners debug malfunctioning code. Similarly, children can use the tools of CS to solve problems couched within stories. Key to these approaches is not teaching CS didactically to early childhood learners, but positioning it as a tool to help such learners engage in play. Still, to accomplish this goal, it is necessary that ECE teachers possess coding skills.

2.2 Preservice Teacher Education

Preservice teacher education is defined as the program of preparation university students need to take to submit for teaching certification in the relevant jurisdiction. Field experience and student teaching have long held a central place within preservice teacher education [11]–[13]. Many teacher education courses contain field experience components, in which teacher candidates visit schools to observe practicing teachers employing techniques being taught in the teacher education course, and the teacher candidates themselves can practice such techniques. Teacher candidates need to learn the complex problem solving that is inherent to teaching [14]–[16]. Mentor teachers can help teacher candidates develop rich actionable knowledge and skill for teaching. But they must balance that mentoring with their own responsibilities to be the lead teacher and bedrock in young children's education [17]. It is not possible for mentor teachers to teach teacher candidates all they need to know about teaching [17]. This leaves preservice teacher educators with a quandary: should one develop teacher candidates' knowledge and skills to a great extent and then have them engage in field experience, or have them develop the needed skill sets all while engaging in field experience. This quandary is a major reason field experience is often couched within teacher education courses that themselves are situated within a block. Research on preparing teacher candidates to integrate technology indicates that field experience in which candidates need to integrate technology is one of the best predictors of future technology integration [12], [18], [19].

2.3 Digital Competence

There is a consensus that schools need to equip the young generation with digital literacy so that they can use the internet critically, creatively, and responsibly, increase their career and social opportunities, and engage in lifelong learning [20], [21]. It is necessary for teachers to become digitally competent themselves in order to optimally use technologies and accompany their students in the development of digital competence [22]. Considering that coding is another language for young children to learn as part of foundational literacy education [9], it is teachers' responsibility to create an environment conducive to their students' development of digital competence as well as literacy. However, mixed findings on learning outcomes suggest that teachers should deliberate on how they can use technology to support student learning [23]. Multiple frameworks have been proposed to better understand and prepare teachers for 21st-century digital competency. The Assessment and Teaching of Twenty-First Century Skills Framework, which emphasizes creative and innovative ways of thinking and solving problems, is one example. Another example is the European Framework for the Digital Competence of Educators, which describes the five areas of competencies every citizen should develop to succeed in a digital society, including information and data literacy and digital content creation [24].

2.3.1 Preservice Teachers' Perceptions of Computer Science

A key reason women often do not pursue CS pathways has to do with their own perceptions of CS, which in turn was informed by society, including their P-12 (i.e., preschool-12th grade) teachers [25]–[27]. Endemic to society's influence in this regard are hidden biases about CS and gender traits [28]. P-12 teachers often associate CS and other technical fields with masculine traits, and this in turn reifies CS as masculine in the minds of learners [28], [29]. For example, CS is often positioned as an individualistic pursuit that involves long hours of working alone and risk-taking [30]. Indeed, even learners who are interested in CS often perceive computer scientists as antisocial and CS as hard, and this may impact their intention to pursue a CS career [30]. Such implicit biases can also influence preservice [31] and inservice teachers' views of who should be encouraged to pursue STEM pathways, including CS.

In 2019, 97.4% of preschool and kindergarten teachers in the USA were women, and this proportion has remained stable over time [32]. Similarly, in most European countries, the early childhood education workforce is composed of almost exclusively women [33]. This has important implications for the teaching of CS in early childhood contexts. Women are drastically underrepresented in CS; indeed, of all the STEM fields, the gender gap is the greatest in CS [25], [34]–[37]. This is due to a myriad of factors including structural factors within CS programs at the elementary, secondary, and university levels [36], [38], [39] and lack of suitable role models [34], [35]. Such factors can make women perceive that they do not belong in CS [34], [40].

Views of the value of digital technologies to early childhood education often vary based on several factors, including teaching experience [41] and a judgment of whether or not the target early childhood learners already have too much technology in their lives [42]. A large study of preschool teachers indicated that the strongest predictor of technology use was attitudes towards the technology, defined as perceptions of the extent to which technologies can contribute to student learning or teacher administrative tasks [41]. Not only the attitudes towards the technology but also other elements such as experience in technology use and competency of technology use are strong predictors of pre-service teachers' technology integration [43]. Notably, those elements are closely associated with broader educational contexts and institutional factors.

One method that has been proposed to address the underrepresentation of women in CS is broadening opportunities for participation in CS [44]. This can be done through the infusion of CS in P-12 curricula [45]. While many high schools offer CS courses, they are usually electives in which few women enroll, at least in part due to the stereotype of CS as masculine [25], [27]. There has been less work done at the early childhood [46] and elementary levels [47]–[49], and much of this has to do with the (lack of) preparedness of teachers to teach CS [50]–[52]. Preparing ECE teachers to teach CS involves not only helping them learn the skills of coding and debugging, but also gain a belief that coding is important to ECE curricula [53].

3 CONCEPTUAL FRAMEWORK FOR PRESERVICE TEACHERS' CS MOTIVATION

Teachers are autonomous human beings whose choices about what to teach and how stem from their own teacher identity, skills, motivation, and constraints. A key predictor of teachers' teaching quality and pedagogical choices is their motivation [54]. While motivation can be thought of from many perspectives, preservice teachers' motivation in this study was approached from the perspective that stereotypical conception about a content domain drives interest in the domain e.g., [55]. Specifically, we constructed the conceptual framework of this study based on the literatures demonstrating (a) the influence of learners' stereotypical conception about a particular domain (e.g., CS) on their interests e.g., [55], and (b) the importance of goal orientation [56]–[59] and emotions [60], [61] in engagement with the domain. Our framework was to guide to study preservice teachers' motivation in a pluralistic way in which multiple factors are considered given the multiple roles of preservice teachers being teachers and learners. But our framework was also to understand CS specific motivation that may influence preservice teachers' views of coding. Considering that teachers' fundamental beliefs about knowledge and knowledge acquisition impact how they teach [62], information of their conception about CS should help not only understand their views of coding but also inform researchers and practitioners how to prepare preservice teachers for teaching of CS. The following sections explain the five major constructs interrelated with teacher CS motivation in our conceptual framework that may impact views of coding.

3.1 Domain Identity

Stereotypical conceptions about domains can be studied through domain identity. Domain identity refers to the phenomenon of deeming that a particular domain aligns with one's self [63]. For example, some students readily identify with the domain of mathematics, seeing mathematics as part of who they are, seeking out opportunities to engage with mathematics-related tasks, and desiring to pursue a career grounded in mathematics. Similarly, students can identify with the domain of English, seeing English as part of who they are, and seeking to pursue an English-related career. Identification with CS has been studied especially gender differences in CS motivation. For example, in Cheryan et al., (2009), many female undergraduates usually identified CS as a domain to which they do not belong. Such identification with CS or lack thereof was also related to their interests or disinterests. Domain identifications of teachers are especially important to consider in elementary and ECE contexts because elementary and ECE teachers, many of who are female, are tasked with teaching the entire curriculum. For example, ECE teachers who do not identify with mathematics often try to shield their students from mathematics [64]. With the inclusion of coding and robotics within ECE, a new consideration for domain identity of ECE teachers is relevant: identification with CS and engineering.

3.2 Interest

The interest individuals hold towards a phenomenon can be defined as the degree to which they find the phenomenon to be compelling and worth researching further [65]. Situational interest refers to interest generated in the moment by a phenomenon, while personal interest refers to an enduring disposition to study a phenomenon [66]. It stands to reason that individuals with interest in CS would be more likely to engage with CS than those with little to no interest in CS. This is especially critical to early childhood education contexts, where CS is an optional subject and is often superseded by such subjects that are the focus of accountability efforts, like mathematics, science, and language arts [67].

3.3 Goal Orientation

According to another prominent motivation theory, individuals' motivation with regards to a task can be explained by their goals in completing a learning task; individuals with mastery goals seek to gain mastery over the content, individuals with performance-approach goals seek to perform better than others, and individuals with performance-avoid tasks avoid performing the task to avoid appearing less competent than others [56], [57]. While mastery goal orientations have long been considered to be ideal [58], much research has shown that performance-approach goals are equally effective in producing strong outcomes [59].

3.4 Academic Emotions

Academic emotions can be defined as positive and negative emotions that learners can experience before and when engaging in learning tasks. When students experience positive academic emotions, like enjoyment, they are more likely to adopt mastery goals [60]. Students who think that they are likely to be successful at an academic task and have high internal control over the outcome are likely to experience anticipatory joy [61]. Meanwhile, students who believe that they are likely to fail at a task and have no control over the outcome are likely to experience hopelessness [61].

3.5 Prior Experience

Just as field experience teaching CS, perceptions of CS, and motivation to teach CS has the potential to predict ECE teacher candidates' views of coding, so too can experience engaging with CS. First, having prior experience with CS may mean that an ECE teacher candidate identified with or had enough interest in CS at least in the past to opt into computer science instruction [68]. But if the CS learning experience reified stereotypes about computing, having had prior experience with CS may predict lower views of coding [26].

4 RESEARCH QUESTIONS

1) How do ECE teacher candidates' views of coding change as a result of learning to use coding in teaching?
2) How can their views of coding be predicted using study, time point (pre-survey versus post-survey), prior programming knowledge and experience, ten latent survey factors, and the inclusion of lesson design/field experience?

5 METHOD

5.1 Participants and Setting

The research was conducted in five different preservice, early childhood education classes from spring 2018 to spring 2020 in two large public universities in the United States. The three classes from university 1 covered integrating the performing and visual arts in early childhood education, while the two classes from university 2 dealt with child's play as educative processes. The robotics and programming units lasted 7.5 hours, except for one study that lasted 5 hours (i.e., study 3 from university 1), and involved robotics in early childhood STEM education and robot programming activities. The number of participants in each study was study 1 = 58 (29.1%), study 2 = 60 (30.1%), study 3 = 43 (21.6%), study 4 = 19 (9.5%), and study 5 = 19 (9.5%), leading to a total sample of N = 199. Participants were mostly female (96%, n = 191; male: 4%, n = 8). Participants' age ranged from 19 to 27 years old (M = 20.41, SD = 1.09). The majority of the participants were White (82.4%; n = 164), 17 (8.5%) were Asian, 7 (3.5%) were Hispanic, 7 (3.5%) were Black, and 4 (2%) participants identified as multi-racial. Most participants majored in Education (98.5%, n = 196; other majors: 1.5%, n=3) and their years of standing were diverse ranging from the first semester to the ninth semester; 2nd year and 3rd year students together represented 70.3% (n = 140) of the participants. Most participants self-reported having no programming knowledge (55.3%, n = 110) or little knowledge (34.7%, n = 69) while 18 participants (9%) reported having intermediate programming knowledge and only 2 participants (1%) reported high programming knowledge. Most participants did not have robot programming experience (89.4%, n = 178) prior to their participation in the present research.

5.2 Robot Programming Unit

The robot programming units shared seven main commonalities in terms of (a) tools, (b) sequence of tasks, (c) collaborative programming, (d) reflection opportunities, (e) contextualization in teaching, (f) emphasis on early learning, and (g) use of examples and models. Specifically, the robot programming activities in the five studies involved the following procedure in general: First, participants took the presurvey before starting the unit, which took about 20-30 minutes. In the first class, participants were introduced to block-based programming and robotics in early childhood education. They then were provided one of the educational robots (i.e., Ozobots) and coding samples for preschoolers and had a chance to practice simple coding on the block-based coding platform (i.e., Ozoblockly) (see Figure 1). Afterward, they discussed the ideas on how to relate robotics activities to children's play and learning. In the second and the third (except for study 3) classes, participants paired up and collaboratively worked on a series of programming tasks that were designed in order of increasing difficulties. The tasks involved either creating code or debugging given code so that it can make the Ozobot perform the desired movement. For example, participants learned to code for square movement first and then rectangle movement because the code structure is typically simpler for a square (e.g., repeat one-side movement 4 times vs. repeat two-side movement 2 times). In the meantime, they were taught basic programming concepts and all their activities were scaffolded with examples and models. After that, they were asked to reflect on the challenges in using Ozobots and programming and to create scenarios or design lessons that integrate coding and robotics into their teaching or play with preschoolers. At the end of the unit, participants took the postsurvey.

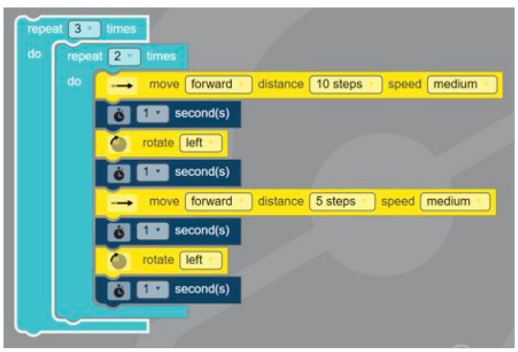

Figure 1: sample practice code (i.e., making rectangle three times) on Ozoblockly platform

There were variations in these studies as well. First, early learning and development standards were integrated into the unit in studies 1-3 with the emphasis of using robots and coding as part of the preschool curriculum. In contrast, the ECE course on play in studies 4-5 focused on learning opportunities that emerge from young children's play. Consequently, there was no formal introduction to the ECE curriculum. Rather, the use of robots and coding in the contexts in which play is the key was highlighted. Second, studies 1-2 had field experience but studies 3-5 did not. Last, unit length in studies 1, 2, 4, and 5 was 7.5 hours, while unit length in study 3 was 5 hours.

5.3 Measures

5.3.1 Presurvey and Postsurvey

All participants completed a survey both before and after learning to program robots. The survey contained 100 closed response questions in University-1 and 102 closed response questions in University-2, and which covered computer programming knowledge, robot programming experience, and STEM and computer science motivation. Two questions from the survey used in University-2 were removed from the analysis to have responses to the same questions between the two sets of studies. The survey contained modified items from such existing instruments as the STEM Semantics Survey [69], the Achievement Emotions Questionnaire – Mathematics (AEQ-M) [70], the Learning Self-Regulation Questionnaire (LSRQ) [71], Patterns of Adaptive Learning Scales (PALS) [72], Domain Identification Measure [73], and Views of Coding [74]. The STEM Semantics Survey was developed based on a sample including teacher preparation candidates from a large Midwest university as well teacher/liaison participants in the Middle Schoolers Out to Save the World (MSOSW) training sessions, the PALs were administered to students and teachers in elementary, middle, and high schools in three Midwest states, and the Views of Coding survey was intentionally designed for students in primary and secondary education majors. Additionally, in the presurvey, participants were asked to report their prior computer programming knowledge and robot programming experience. Our aim was to investigate ECE teacher candidates' views of coding in ECE contexts that could be improved through learning to program robots and motivation. As described earlier, we examined motivation from a pluralistic perspective in which multiple factors comprise one's motivation [88, 89]. We thus assessed ECE teacher candidates' interests, emotions, goal orientations, and domain identifications related to STEM and CS to study multifaced motivation in addition to their views of coding. We then conducted principal component analysis to reduce the number of variables across these instruments while preserving the needed dimensionality of data.

5.3.1.1 *Computer programming knowledge and robot programming experience*

All participants were asked to report their computer programming knowledge and robot programming experience in the pre-surveys. The four-level of computer programming knowledge was coded as no knowledge = 1, low knowledge = 2, intermediate knowledge = 3, and high knowledge = 4. As for robot programming experience, participants' responses were coded as Yes = 1 or No = 2.

5.3.1.2 ***Motivation variables***

Principal component analysis using varimax rotation was conducted with 214 preservice early childhood teachers' responses to the pre-surveys, consisting of one hundred items. Note that n = 214 for the presurvey, but n = 199 for the set of participants who completed the presurvey and postsurvey. The determinant was different than zero, the KMO was 0.854, and Bartlett's Test of Sphericity was significant ($p < 0.001$). The ten latent variables accounting for 61.93% of the variance were determined based on 0.30 as cut-off score, Kaiser's criterion of eigenvalues [75], and parallel analysis. Ten latent variables were identified:

Perceptions of mathematics included fourteen items (Cronbach's α = 0.954). This factor pertained to students' mathematics interest and identification with mathematics, and contained items from two different scales. The factor included slightly modified items from the Mathematics - Domain Identification Measure (DIM) survey to which participants responded using a 5-point Likert scale [73, p. 1054]. Specifically, we changed a couple of items with an interrogative sentence in the original scale (e.g., How much is Math to the sense of who you are?)

to a declarative sentence (e.g., Math is important to the sense of who I am). Smith and White [73] reported high reliability for the original subscale (Cronbach's α = 0.93) for the Mathematics-DIM. Authors [76] demonstrated high reliability for the slightly modified Mathematics-DIM survey conducted among ECE majors (Cronbach's α = 0.95). This factor also included items from the mathematics interest scale [69]. A sample item invited respondents to rate the item "To me, MATH is unexciting: is exciting" on a 7-point Likert scale [69, p. 350]. High Cronbach's α values were calculated before for the original mathematics interest scale (0.86 – 0.92) [69], [76], [77].

CS and Engineering emphasis in STEM career had thirteen items (Cronbach's α = 0.949). This factor covered interest in STEM career emphasizing computer science and engineering. A sample item invited participants to use a 7-point Likert scale to rate "To me, A CAREER in science, technology, engineering, mathematics, or computer science is unappealing: is appealing" [69, p. 350]. High Cronbach's α values were calculated before for the original engineering (0.80 - 0.92) and career (0.76 – 0.93) interest scales [69], [76], [77] among a wide range of samples including ECE majors. The computer science scale used the same adjective pairs with other scales in [69]. Authors [76] calculated high reliability (Cronbach's α = 0.94) for the computer science interest scale.

Perceived value of coding had eighteen items (Cronbach's α = 0.916). This factor was about attitudes toward coding skills, understanding of coding, and autonomous regulation. The factor included slightly modified items from two surveys: The Learning Self-regulation Questionnaire (LSRQ), in which participants used a 5-point Likert scale to respond to items such as *I felt like participating in STEM-related class activities was a good way to improve my understanding of STEM-related topics* (we changed a word 'patients' in the original scale into 'STEM-related topics' according to our research domain) with 5-point Likert scale in Black and Deci [71], reporting Cronbach's α as 0.80 and a survey related to views of computing (e.g., I would voluntarily take courses on coding if I were given the opportunity) with 4-point Likert scale in [74]. Here we used a word 'coding' instead of the word 'computing' in the original scale. Authors [76], [77] reported acceptable reliability for the slightly modified LSRQ (Cronbach's α = 0.71 and Cronbach's α = 0.71). Yadav et al. [78] and Authors [76] calculated Cronbach's α values (0.76 and 0.94, respectively) for the modified version of the survey related to views of computing.

Perceptions of technology and engineering had twelve items (Cronbach's α = 0.874). This factor was about interest in and identification with technology and engineering. The factor included original items from [69] and slightly modified items from [71] and [79] where we added examples of technology (i.e., computer software) and engineering (i.e., building robots) to the original item. A sample item invited participants to use a 7-point Likert scale to rate "To me, TECHNOLOGY is unappealing : is appealing" [69, p. 350]. High Cronbach's α values were calculated before for the original technology (0.77 - 0.95) and engineering (0.80 – 0.92) interest scales [69], [76], [77]. This factor included slightly modified items from the Computer Technology - DIM survey (e.g., Engineering involves working with other people) in Smith et al. [79, p. 350] and the LSRQ (e.g., A solid understanding of STEM-related topics was important to my intellectual growth) in [71] with 5-point Likert scales. Smith et al [79] and Black and Deci [71] reported Cronbach's α values for the original surveys (0.78 and 0.80, respectively). Authors [76] calculated Cronbach's α = 0.635 and Cronbach's α = 0.71 for the slightly modified Computer Technology – DIM survey and the LSRQ, respectively.

Performance goal orientation had nine items (Cronbach's α = 0.896). This factor was about performance avoid (e.g., "It's important to me that I don't look stupid in class") [72, p. 13] and performance approach (e.g., "It's important to me that I look smart compared to others in my class”) [72, p. 12] goal orientations. Midgley et al. [72] and Authors (2021) calculated Cronbach’s α values for performance avoid (0.74 and 0.72, respectively) and performance approach (0.89 and 0.82, respectively) for the original 5-point Likert scale.

Perceptions of English had seven items (Cronbach’s α = 0.917). This factor was about identification with the subject *English*. The slightly modified items were from the English - DIM survey (e.g., It is important to me to be good at English) with 5-point Likert scale in Smith and White [73, p. 1054]. Smith and White [73] reported Cronbach’s α as 0.90 for the original survey. Authors [76] calculated Cronbach’s α = 0.80 for the slightly modified English – DIM survey.

Science interest had six items (Cronbach’s α = 0.890). The factor was about interest in science. A sample item was rating “To me, SCIENCE - is unappealing : is appealing” [69, p. 350]. Cronbach’s alpha value was calculated 0.84 before for the 7-point Likert scale [69]. High Cronbach’s α values were calculated before (0.86 and 0.91, respectively) in [76], [77]for the science interest scale. The slightly modified item in this factor was from the LSRQ (e.g., I would feel bad about myself if I didn’t do STEM-related class activities) with 5-point Likert scale. William and Deci [80] reported Cronbach’s α as 0.75 for the original the LSRQ.

Mastery goal orientation (MGO) had five items (Cronbach’s α = 0.897). The factor was about achievement goal orientation (e.g., “One of my goals in class is to learn as much as I can”) [72, p. 11]. Cronbach’s alpha value was calculated as 0.85 [72] and 0.91 [76]before for the original MGO scale with the 5-point Likert scale.

Achievement emotion in STEM+CS had nine items (Cronbach’s α = 0.913). This factor was about achievement emotions in STEM and attitudes toward coding skills. The factor included slightly modified items from the Achievement Emotions Questionnaire – Mathematics (AEQ-M) (e.g., I look forward to my STEM-related class) with the 5-point Likert scale [70, p. 7] and from a survey related to views of computing (e.g., I am not comfortable with learning how to code) with 4-point Likert scale [74]. Pekrun et al. [70] reported a high reliability (Cronbach’s α = 0.90) for the original AEQ-M. Authors [76], [77] reported Cronbach’s α as 0.89 and 0.91, respectively, for the slightly modified AEQ-M scale.

Identification with CS and Engineering had four items (Cronbach’s α = 0.706). This factor pertained to identification with computer science and engineering. The slightly modified items were from the Computer Technology - DIM survey (e.g., Engineering (e.g., building robots) is masculine) with 5-point Likert scale in Smith et al. [79, p. 350]. Smith et al. [79] reported Cronbach’s α to be 0.78 for the original survey.

5.3.2 Open-ended items

Participants were invited to respond to the following three items modified from the open-ended items (i.e., substituting the word ‘coding’ for ‘computational thinking’ in the original questions) on the original views of coding survey [74, p. 470]:

In your view, what is coding? What is its purpose?

In your view, how can (or cannot) coding be integrated in preschool classrooms?

In your view, how does coding relate to disciplines and fields other than computer science? Please provide an example.

We included these questions because they provided the opportunity to gain detailed insight into participants’ perceptions and knowledge of coding and how it can be used in early childhood education classrooms that cannot be captured fully by the closed-ended items.

5.4 Data Analysis

5.4.1 Dummy Coding

Data came from five independent studies spanning two different universities. As such, the classes studied had some differences in implementation and requirements (see the Robot Programming Unit section). The five studies were coded from study 1 to study 5. Three of the studies required participants to create a lesson plan and had a field experience component (dummy coded as 1), while two did not require participants to write a lesson plan and did not have a field experience component (dummy coded as 2). The 'time' variable was the order in which the participants took the survey. Time points for pre-survey and post-survey were dummy coded as 1 and 2, respectively.

5.4.2 Open-ended Response Evaluation

199 participants' responses to the open-ended items on the pre and postsurvey were evaluated with a rubric (Appendix A). Scores from zero to four were assigned to the response of each item; 0 representing no response, and 4 representing a good understanding of coding, how to integrate coding into preschool, and how coding relates to other fields other than computer science. For views of the nature of coding, we considered the following response that 'coding is the sequence of numbers, commands, and signals that tell computers what to do' as evidence of the participant having a sound understanding of the subject. Therefore, we assigned the response a score of 4. We scored a response such as 'coding involves making a computer function' a score of 3 because the participant responded only to one of the sub-questions asked and the response was fairly general. A response such as 'it's computer related. Beyond that I don't know what it's for' was rated 2 because it indicates a basic understanding but also significant lack of prior knowledge of coding. A response such as 'I'm not really sure of what it is. In private school, we did not have any computer science classes,' the response would be rated as 1, because it indicated that the participant did not know how to answer the question. If the participant did not enter any information in the open-ended question, the response would be automatically assigned a score of 0. More information on scoring criteria and example responses can be found in Appendix A.

Once the evaluation rubric was developed, all four raters went through the rubric to ensure a consistent understanding of the rubric. Then pilot coding was conducted: each rater was paired with another rater and completed a different portion of the rating from both pre- and post-survey responses across multiple studies for a few times. The paired rater was different each round, so the raters developed a shared understanding of the coding rubric. During the pilot coding process, four raters evaluated participants' responses independently using the rubric and the consensus was reached. Then, two raters were paired up, and their evaluation scores were used to calculate the interrater reliabilities. The first pair rated approximately 60% of the data and the second pair rated 40% of the data. For each pair of raters, the Cohen's Kappa scores of ratings for pairs before consensus were 0.767 and 0.854. Consensus scores were used in the analysis as the outcome variable.

5.5 Analytic Strategy

We used geepack package [81] for R to conduct generalized estimating equation analysis. We chose to use a generalized estimating equations approach because we wanted to use predictor data to predict an outcome, but the participants were nested within different classrooms and universities. In addition, participants' views of (a) nature of coding, (b) integration of coding in preschool classrooms, and (c) relation of coding to non-CS fields in the post-survey is likely to be correlated with their view in the pre-survey. As such, using a standard regression approach would not work [82]. Generalized estimating equations can account for nesting and as such produces minimally biased Betas [82]. Generalized estimating equations offer numerous advantages for modeling correlated data [83]. The interpretation of the estimates is identical to those in models with uncorrelated data [83].

The predictor variables included: a) study in which ECE teacher candidates participated, b) prior programming knowledge, c) prior robot programming experience, d) scores for the ten latent factors from the presurvey, and e) inclusion of lesson design plus field experience or not. These measurements were hypothesized to be related to ratings of open-ended response items at the second time point (i.e., post-survey). Note that item (e) is related to item (a) but there were multiple studies in which lesson design plus field experience was used, and so it was important to keep study ID as a predictor to account for potential nesting. Prior literature indicated that prior programming knowledge, prior robot programming experience, and motivation predict preservice teachers' views of coding. The gap between pre-survey (time = 1) and post-survey (time = 2) was around three weeks. Study = 0 was used as the baseline comparison group for study in which participants were enrolled. Time = 1 (pre-survey) was used as the baseline comparison group to the post-surveys for the difference in participants' views of coding.

We used AR-1 correlation structure because we speculate that one's post-survey score is correlated with his or her pre-survey score. Identity link function was used because our outcome variable is continuous.

6 RESULTS

6.1 RQ1: How do ECE teacher candidates' views of coding change as a result of learning to use coding in teaching?

Participants' overall views of coding scores increased significantly from pre to posttest for all five study groups (see Figure 2). However, study was not a significant predictor for an increase in open-ended response scoring. The increase rate was highest among participants who were enrolled in study 3. By contrast, the lowest rate was found among participants in study 1.

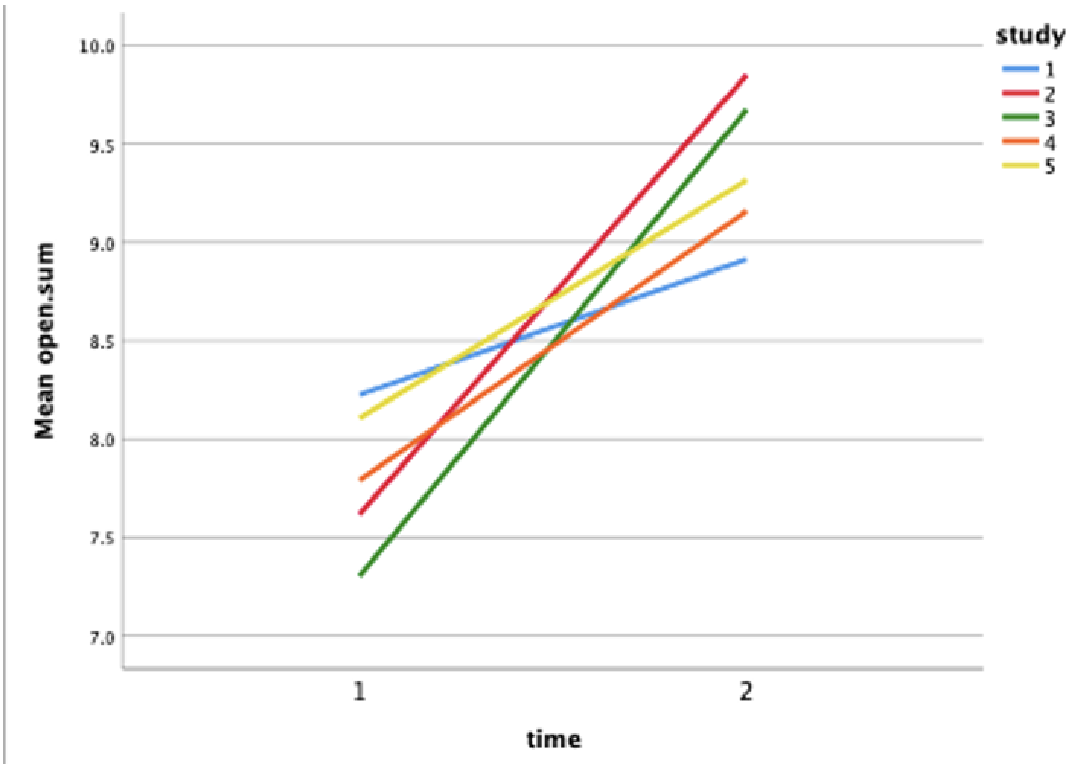

Figure 2: Pre-post gains in total open-ended response scores

6.2 RQ2: How can ECE teacher candidates' views of coding be predicted using study, time point (pre-survey vs. post-survey), prior programming knowledge and experience, ten latent survey factors, and the inclusion of lesson design/field experience?

Table 1: Descriptive Statistics of the Full Score and Score of Each Question

Variable	M	SD	Range
Full Score	8.61	2.09	0-12
Views of the nature of coding	2.98	0.77	0-4
Views of integration of coding in preschool	2.84	0.997	0-4
Views of relation of coding to non-CS fields	2.79	1.129	0-4

Table 2: Descriptive Statistics of Significant Predictors

Variable	M	SD	Range
Perception of value of coding	44.36	9.71	18-69
Perception of mathematics	49.67	16.49	14-79

6.3 Predicting Overall Views of Coding Scores

There were four significant predictor variables including time points, programming knowledge, robot programming experience, and views of coding. Specifically, the time variable was significantly positively associated with open-ended response total scores ($\beta = 1.633$, $p < 0.001$), indicating that overall views of coding scores significantly increased from pre- to post-survey. Robot programming experience was also a significant positive predictor of the total scores in the post-survey ($\beta = 1.226$, $p = 0.002$), such that participants who answered that they have prior robot programming experience scored 1.226 units better in open-ended responses in the post-survey than participants who reported no prior robot programming experience. Perceptions of the value of coding was also significantly positively related with open-ended response total scores in the post-survey ($\beta = 0.040$, $p = 0.005$), indicating the more positive perceptions of the value of coding participants have the higher scores the participants received in their open-ended responses in the post-survey. However, programming knowledge was significantly negatively associated with open-ended response total scores in post-survey ($\beta = -1.091$, $p = 0.018$), particularly participants who reported having intermediate programming knowledge obtained 1.091 unit less on open-ended response total scores in post-survey than participants who reported no prior programming knowledge.

Table 3: Predictors of Total Views of Coding Score

Predictor	Beta	Std.err	Wald	Pr(>|W|)
(Intercept)	5.1	1.04	23.82	< .001
Time = post-survey	1.63	0.18	82.89	< .001
Study2	0.22	0.26	0.71	0.4
Study3	0.33	0.54	0.38	0.536
Study4	0.41	0.56	0.54	0.461
Study5	0.65	0.57	1.32	0.25
Lesson design and field experience present	-0.57	0.49	1.31	0.253
Low prior programming knowledge	0.06	0.2	0.08	0.778
Intermediate prior programming knowledge	-1.09	0.46	5.59	0.018
High prior programming knowledge	-1.19	0.67	3.19	0.074
Has prior robot programming experience	1.22	0.4	9.5	0.002
Perceptions of mathematics	-0.01	0.01	1.68	0.195
CS & engineering in STEM career	-0.004	0.01	0.23	0.632
Perceived value of coding	0.04	0.01	7.71	0.005
Perception of computer science and technology	0.002	0.01	0.04	0.839
Performance goal orientation	-0.01	0.01	0.53	0.466
Perceptions of English	-0.001	0.02	0.005	0.941
Science interest	0.02	0.01	1.12	0.291
Mastery goal orientation	0.03	0.03	1.01	0.315
Self-determination in STEM+ computer science	0.01	0.02	0.3	0.585
Identification with computer science & engineering	0.02	0.03	0.4	0.528

6.4 Predicting Views of the Nature of Coding

The multivariate generalized estimating equation model detected three significant predictor variables including time, programming knowledge, and robot programming experience. To be specific, the time variable was significantly positively associated with Q1 scores ($\beta = 0.261$, $p < 0.001$), where participants' scores for the same Q1 were significantly higher in post-survey than in pre-survey. Robot programming experience was also a significant positive predictor of Q1 scores in post-survey ($\beta = 0.421$, $p = 0.005$), indicating that participants who reported as having prior robot programming experience have significantly higher scores in Q1 responses than the participants who reported as having no experience. However, programming knowledge was a significant negative predictor of Q1 scores, where participants who reported themselves as having high programming knowledge and intermediate programming knowledge respectively scored 0.778 unit and 0.631 unit less than the participants who reported as having no programming knowledge in Q1 responses in post-survey ($\beta = 0.778$, $p = 0.003$; $\beta = -0.631$, $p < 0.001$).

Table 4: Predictors of View of the Nature of Coding

Predictor	Beta	Std.err	Wald	Pr(>|W|)
(Intercept)	1.65	0.47	12.47	< 0.001
Time = post-survey	0.26	0.07	14.82	< 0.001
Study2	-0.11	0.1	1.29	0.255
Study3	0.12	0.23	0.28	0.593
Study4	0.04	0.22	0.03	0.868
Study5	0.23	0.26	0.77	0.379
Lesson design and field experience present	-0.27	0.21	1.67	0.197
Low prior programming knowledge	-0.09	0.09	1.19	0.274
Intermediate prior programming knowledge	-0.63	0.19	10.89	0.001
High prior programming knowledge	-0.78	0.26	9.09	0.002
Has prior robot programming experience	0.42	0.15	7.63	0.006
Perception of math	0.0001	0.003	0.003	0.958
CS & engineering in STEM career	-0.002	0.003	0.53	0.45
Perceived value of coding	0.009	0.005	3.09	0.079
Perceptions of computer science and technology	-0.00004	0.005	0.00006	0.993
Performance goal orientation	-0.001	0.006	0.05	0.823
Perceptions of English	0.009	0.008	1.25	0.263
Science interest	0.01	0.007	2.53	0.111
Mastery goal orientation	0.009	0.01	0.38	0.538
Self-determination in STEM+CS	0.007	0.009	0.66	0.417
Identification with CS & engineering	0.01	0.013	0.65	0.421

6.5 Predicting Views of Integration of Coding in Preschool

We detected two significant predictor variables including time and perceptions of mathematics. The time variable was significantly positively associated with Q2 open-ended response scores ($\beta = 0.688$, $p < 0.001$), showing participants scored significantly higher in post-survey Q2 responses than in pre-survey responses. However, perception of mathematics (Factor 1) was significantly negatively related to Q2 response scores (β = -.008, p = 0.033), indicating that the more positive perception of mathematics was, the lower the scores participants obtained on views of integration of coding in preschool.

Table 5: Predictors of views of integration of coding in preschool

Predictor	Beta	Std.err	Wald	Pr(>|W|)
(Intercept)	1.97	0.46	18.58	< 0.001
Time = post-survey	0.69	0.09	56.08	< 0.001
Lesson design and field experience present	-0.23	0.23	0.99	0.319
Study2	0.06	0.13	0.22	0.637
Study3	0.22	0.26	0.74	0.389
Study4	0.08	0.26	0.08	0.774
Study5	0.18	0.25	0.53	0.465
Low prior programming knowledge	-0.04	0.1	0.16	0.688
Intermediate prior programming knowledge	-0.26	0.19	2.04	0.153
High prior programming knowledge	-0.26	0.37	0.52	0.472
Has prior robot programming experience	0.39	0.21	3.38	0.066
Perceptions of mathematics	-0.01	0.004	4.53	0.033
CS & engineering in STEM career	0.001	0.004	0.1	0.748
Perceived value of coding	0.01	0.01	3.26	0.071
Perceptions of computer science and technology	0.001	0.01	0.02	0.878
Performance goal orientation	0.003	0.01	0.3	0.582
Perceptions of English	0.001	0.01	0.01	0.937
Science interest	-0.007	0.01	0.65	0.421
Mastery goal orientation	0.02	0.02	1.22	0.268
Self-determination in STEM+CS	0.01	0.01	0.51	0.475
Identification with CS & engineering	-0.02	0.02	1.02	0.312

6.6 Predicting views of relation of coding to non-CS disciplines

Time (β = 0.68, $p < 0.001$) and perceptions of the value of coding (β = 0.02, p = 0.013) were significant predictor variables of views of how coding relates to field other than computer science in the post-survey. Participants scored significantly higher in post-survey open-ended responses to how coding relates to fields other than computer science than the same item on the presurvey.

Table 6: Predictors of views of relation of coding to non-CS disciplines

Predictor	Beta	Std.err	Wald	Pr(>|W|)
(Intercept)	1.48	0.63	5.55	0.018

Time = post-survey	0.68	0.1	48.79	<0.001
Study2	0.27	0.16	2.91	0.088
Study3	-0.02	0.29	0.003	0.954
Study4	0.3	0.25	1.44	0.229
Study5	0.24	0.28	0.72	0.396
Lesson design and field experience2	-0.06	0.23	0.07	0.794
Low prior programming knowledge	0.19	0.12	2.42	0.12
Intermediate prior programming knowledge	-0.19	0.25	0.63	0.427
High prior programming knowledge	-0.15	0.46	0.11	0.744
Has prior robot programming experience	0.41	0.22	3.59	0.058
Perceptions of mathematics	-0.002	0.004	0.13	0.72
CS & engineering in STEM career	-0.003	0.005	0.33	0.562
Perceived value of coding	0.02	0.008	5.41	0.02
Perceptions of computer science and technology	0.001	0.007	0.05	0.818
Performance goal orientation	-0.01	0.008	1.91	0.166
Perceptions of English	-0.01	0.01	1.1	0.295
Science interest	0.01	0.01	1.77	0.184
Mastery goal orientation	0.006	0.02	0.1	0.757
Self-determination in STEM+CS	-0.002	0.01	0.03	0.869
Identification with computer science and engineering	0.02	0.02	1.81	0.178

7 DISCUSSION

Time (pre-survey vs. post-survey) is a significant predictor in all four models, which predicted participants' overall views of coding, views of the nature of coding, views on the integration of coding in preschool, and views of the relation of coding to fields other than CS. Holding all the other variables constant, participants had an improved understanding of coding and its purpose after they worked through the robot programming unit. Holding all the other variables constant, participants had a better understanding of how they can integrate coding into preschool classrooms after they worked through our tasks in this research project. Holding all the other variables constant, participants had a better understanding of how coding can be transferred into other fields after they worked through the robot programming unit. This is promising because views of coding are often closely held and difficult to change [28], [30], [35] From a teacher education perceptive, one might surmise that time would have an effect in university one due to its inclusion of field experience, but not university two. If that were the case, one would expect the variable to not be a significant predictor. That these teacher candidates began to espouse a richer view of coding and to see coding as a valuable part of the preschool curriculum that is applicable to other subjects bodes well for their potential as early childhood CS teachers. In this way, they may also serve as positive role models of female computer scientists, which is critical to countering views of CS as masculine and uninviting for women [26], [84].

Also of note is that designing a lesson and using it in field experience was not a significant predictor for overall views of coding, views of the nature of coding, views of integration of coding in preschools, and views of relation of coding to non-CS fields. Much teacher education literature holds that integrating field experience and lesson design within teacher education courses increases the depth with which teacher candidates learn content [18],

[85]. It is possible that either designing the lesson plan and using it in field experience was not impactful, or that it was but less time spent engaging directly with pair programming [86] counterbalanced that impact. Further research is needed to explore this finding.

Participants with intermediate and high programming knowledge scored significantly lower than participants with no prior programming knowledge on open-ended views of coding responses. In this way, the use of educational robotics and coding in our project was more beneficial for novice programmers than participants who already had some level of knowledge, especially on their understanding of coding and its purpose. For participants with no prior programming experience, learning to use coding in teaching can be a novel and insightful experience for them to develop a better understanding of the role of coding in early childhood education. However, for the participants who already have some programming knowledge, learning to use educational robotics and coding might have a limited impact on their views of coding. Participants with intermediate and high programming knowledge are likely to have taken a CS class before and presumably saw CS as a distinct discipline that is hard and not suitable for early childhood education. Participants were probably constrained by the initial ideas about the nature of coding and had difficulty being creative and flexible in viewing coding from the perspective of early childhood education purpose [87]. In addition, participants with prior experience of coding tend to bring certain expectations about the class based on their prior experience (mostly with text-based programming languages) and if the class is different from what they expected (e.g., class using block-based programming language), they may perceive the class as not inviting or not useful for them, which the literature indicates can lead to weaker views of coding [26], [88]. Last, we speculate that it is possible that those participants might have overestimated their programming knowledge level, given that this estimation was based on participants' self-report. Further research is needed.

We found a small negative association between perception of mathematics and views of integration of coding in preschool. Teacher candidates have a unique identity in that they pursue teaching careers with having a teacher mindset and yet are still students who might not have a clear idea of what they could do or would do as a future teacher. With less knowledge and skills for teaching, they often teach principles similar to how they learned the principles [89]. Also, it is possible that teacher candidates may not have a profound understanding of how concepts and practices from different principles are integrated for the purpose of teaching. Particularly, students with a more positive perception of mathematics are more likely to have higher satisfaction with the way they learned mathematics and prefer teaching using traditional procedures than integrating new teaching tools or approaches. It is probable that they considered integrating coding into early childhood classrooms unnecessary since coding was not part of early learning and development standards [90].

Perceived value of coding has a small relationship with views of the relation of coding to non-CS disciplines. With their positive perception of the value of coding, the participants seemed capable of detecting and recognizing the broad application of coding in other subject areas other than CS. Thus, participants who held a more positive view of coding tended to report that coding could be integrated into other disciplines and were more able to provide better rationales.

7.1 Limitations and Delimitations

Survey responses were collected from early childhood teacher candidates taking teacher preparation courses at two different universities. While the robot programming units had substantial similarities, the teacher education courses had different emphases. We accounted for nesting using generalized estimating equations.

But such nesting can adversely affect the intuitiveness of the interpretation of findings. For example, time is a significant predictor in all four models. While further research is needed to investigate further the nature of the learning activities that led to the positive changes, these findings offer critical implications for teacher education researchers and practitioners who are interested in broadening participations in STEM. As discussed earlier, views not only on CS but also on its value are not easy to change [28], [30], [35]. Two or three 2.5-hour class sessions on coding in this research led to drastic changes in the participants' views of coding. Given positive changes in their views of the value of coding in education, it is possible that these future teachers would actually integrate coding in their classrooms considering the importance of teacher beliefs in technology integration [91, p. 201]. Future research that employs a larger sample size and can link participants' views of coding and their teaching would be valuable.

All data, except dummy coded variables such as time and study, were collected using a self-report survey. Particularly regarding the self-reporting prior programming knowledge and experiences, participants could have been equipped with different understandings of what 'low/intermediate/high' programming knowledge and experiences represented. We might have future participants elaborate on their prior knowledge and experiences using open-ended questions to leverage the self-reported information. Self-presentation bias is an issue in many areas of research with human participants, and no less so in teacher education research [92]. Still, the nature of many of the variables (e.g., science interest, perceptions of CS and technology) studied in this research lend themselves well to self-report.

8 CONCLUSION

Early childhood teacher candidates' views of coding, the place of coding in the preschool curriculum, and the relationship of coding to other disciplines increased after spending only several hours learning to code and use coding in early childhood teaching. This trend was consistent across all five study groups. As highlighted above, this is noteworthy given how resistant women's views of coding are to change [26], [28]. The remaining positive predictors – prior robot coding experience and perceptions of the value of coding – were aligned with the existing literature. Still, the negative predictors – intermediate and high prior programming knowledge and perceptions of mathematics – were not expected. Further research is needed to understand the why behind these predictors. This is an important first step towards, but certainly not the only step needed for, ensuring that CS is for all [45].

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11 HISTORY DATES

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