# Chapter 5
# Virtual Professional Development Enhances Elementary Teacher' Coding Skills and Self-Efficacy:
## A Comparison of Three Models

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## ABSTRACT

*This chapter presents results from a study addressing the growing importance of coding skills in early childhood education. Focused on virtual professional development (PD) models, this study explores the effectiveness of synchronous and asynchronous approaches in enhancing coding skills and self-efficacy among educators. In comparing these models, results reveal significant growth in both, with synchronous models excelling in fostering self-efficacy growth. Noteworthy is the impact of facilitators, with peer-led models enhancing coding skills and expert-led*

DOI: 10.4018/979-8-3693-2377-9.ch005

*models boosting self-efficacy. The compensatory pattern observed in educators with coding experience adds nuance. However, mediation analyses indicate that factors beyond self-efficacy contribute to educators' competency. Implications include advocating for virtual PD adoption, tailoring programs to specific coding experiences, and further exploration into the multifaceted dynamics of educators' competency and self-efficacy.*

## INTRODUCTION

Recently, there has been an increase in the integration of developmentally appropriate computer science education in early childhood, mirroring the societal recognition of coding and computational thinking (CT) as important skills (Author, 2017; Author et al., 2022). Coding tools specifically designed for young children have benefits that extend beyond an exposure to programming and might prove valuable across diverse subject areas and problem-solving domains (Author, 2017; Mihm, 2021). ScratchJr, the leading introductory programming language, is a developmentally appropriate interactive platform that provides a coding playground for kids aged 5-8 during the teaching of coding concepts and the development of CT (Author, 2020; Author & Resnick, 2015). CT skills encompass problem-solving skills like deconstruction, abstraction, pattern recognition, and algorithms (Hudin, 2023; Resnick, 2018; Wing, 2011).

However, in order to integrate the use of tools such as ScratchJr in the classroom, pedagogical approaches that are consistent with play-based, creative learning are needed. The Coding as Another Language (CAL) curriculum recognizes the power of expression through creating meaningful, shareable computational projects in addition to the benefit of learning to code and developing critical thinking and CT skills (Author, 2019). CAL recognizes coding not only as a tool to solve problems, but as a literacy through which kids can tell stories, express themselves, and learn about themselves and the world. CAL contains lesson plans to support K-2 teachers as they integrate the pedagogy and coding tools into their classrooms in a developmentally appropriate and playful way (Author et al., 2023). This guiding framework and pedagogy are necessary resources for teachers to learn how to introduce technology tools such as ScratchJr in a way that positively impacts their students' development. To read more about the CAL approach and view the curriculum, please visit: sites.bc.edu/codingasanotherlanguage.

While there is widespread support among teachers, principals, and superintendents for incorporating computer science (CS) into school curricula, a significant challenge arises from the reported lack of educators equipped with the necessary skills and training to teach CS (Mouza et al., 2022). Teachers often express a lack of confidence and competence in teaching coding, citing gaps in subject knowledge, unfamiliarity with teaching approaches, and insufficient support and confidence as recurring challenges, even after participating in training courses (Codding et al., 2021; Kong & Wong, 2017; Mouza et al., 2022; Singh, 2018; Wang et al., 2020). This holds utmost importance as recent studies emphasize the role teachers' conference plays, not only in shaping their teaching approaches but also in impacting their students' academic achievements (Hassan, 2019; Pandey & Kumar, 2020). This underscores the pressing need for teacher training designed to equip teachers with the skills and confidence necessary.

A recent meta-analysis found that professional development (PD) in the K-12 STEM context are effective in increasing teachers' confidence (Zhou et al., 2023). The potential benefits of high-impact PD are noteworthy, encompassing improved student performance, reduced dropout rates, and other positive outcomes (Shaha et al., 2016). However, challenges associated with traditional in-person training, such as accessibility and cost, limit their wider adoption (Mihaly et al., 2022). Virtual PD emerged as a promising approach to providing flexibility and sustainable opportunities to increase teachers' access to high-quality training, particularly in the COVID-19 era (Bragg et al., 2021). In the following section we delve into the literature on various modalities of PD for teachers and outline the objectives of the study.

## LITERATURE REVIEW

### Teacher Professional Development

The traditionally accepted in-person PD model, led by an expert facilitator, offers a unique environment where educators can engage in dynamic discussions, collaborate with peers, and receive immediate feedback—a combination proven to enhance the transfer of knowledge into classroom practice (Patterson et al., 2020; Rodgers et al., 2019). However, with the increasing demand for high-quality PD comes a set of challenges associated with in-person training that hinder their broader implementation (Mihaly et al., 2022). The in-person PD model introduces logistical scheduling challenges, proves inaccessible for certain rural or underfunded schools, and exhibits limitations in relevance, applicability, and scalability (Hill, 2015). Moreover, the associated costs with in-person workshops and coaching structures range from \$138.29 to \$158.45 per contact hour for workshops and \$169.43 for coaching (Barrett & Pas, 2020). This traditional PD model represents a significant financial investment for school districts, with estimated costs of \$18,000 per teacher per year (Mihaly et al., 2022). Access and cost barriers often constrain the reach of these valuable opportunities, limiting the broader implementation of effective PD initiatives.

It is thus necessary to find alternative models of PD that are more efficient, but just as effective (Miller et al., 2019). In recent years, mobile learning, also referred to as m-learning, has emerged as a viable alternative to in-person learning (Dahri et al., 2022). We define m-learning as the use of portable devices such as cellphones and laptops to access information in any location or while on the move, which is in contrast to the traditional classroom setting. These systems, serve as a valuable solution for overcoming barriers related to distance, geography, environment, and infrastructure (Dahri et al., 2022; Traxler & Vosloo, 2014). M-learning has the versatility to operate in both online and offline settings, offering a comparable level of effectiveness to in-person PD in enhancing teachers' knowledge, attitude, and beliefs (Chen & Cao, 2022; Lawrence & Ogundolire, 2022). This exploration forms the basis of our inquiry into the diverse alternative modalities of PD training, seeking to understand not only their effectiveness but also their potential to overcome the barriers that limit widespread access.

In the realm of m-learning, diverse models come into play. An online, synchronous workshop, guided by a facilitator, eliminates the need for in-person travel, a common hurdle for PD accessibility. This breaks down geographical barriers by allowing teachers from various schools to partake without the necessity of physical travel. Research consistently underscores the effectiveness of synchronous, online PDs in enhancing both teacher knowledge and self-efficacy

*(Jin & Harron, 2023; Kapoor et al., 2023; Mouza et al., 2022). Further, specific features inherent in the synchronous model, such as collaborative engagement within a group of knowledgeable peers and participation in joint activities, mirror the features of in-person training.*

Within synchronous models, a further distinction can be made between PD models led by expert facilitators and those led by trained peer facilitators. For PDs involving highly technical content, an expert in the field appears to be the ideal option. However, this is extremely costly and sometimes not possible to achieve. Hassler et al. (2018) examined the possibility of training peers to lead PD, specifically in low-resourced areas where an expert facilitator might not be an option, finding peer facilitation to be effective, as long as they are properly trained. Another option is to create a collective learning environment in which teachers all engage in teaching each other (Campbell, 2014).

While synchronous online PDs allow for real-time interaction and immediate feedback, they require adherence to a schedule, the presence of a facilitator, and may lack individualization (Moser & Smith, 2015). A scalable and adaptable option is a completely online and asynchronous self-paced course. This is the most accessible option, particularly when offered free of charge, requiring no logistical coordination between learners and facilitator. These studies collectively underscore the potential of a fully asynchronous PD model to address the diverse needs of learners and improve learning outcomes. Polly (2015) demonstrated the successful use of asynchronous online instruction to develop elementary school teacher-leaders' knowledge of mathematics content and pedagogies. While there is an argument in favor of the synchronous model, citing its collaborative nature and real-time feedback (Goode et al., 2020; Sun et al., 2023; Zheng et al., 2019), Marchisio et al. (2018) brought attention to the significant role of online asynchronous collaboration. They emphasized its contribution to enhancing teacher professional knowledge and competencies, particularly within the realm of in-service teacher training.

Overall, there are many existing schools of thought regarding the comparison between in-person versus virtual PDs. Sentence and Csizmadia (2017) argue that face-to-face PD holds particular significance for teachers lacking experience in CT and coding and feeling particularly apprehensive about teaching these subjects. In contrast, Vitale (2010) underscores the efficacy of virtual PD, highlighting the importance of course engagement and online communication strategies between faculty and students, especially beneficial for novice educators and online faculty mentors. This becomes particularly relevant in situations where virtual PDs become the only viable option, such as during the COVID-19 pandemic or for teachers situated in rural locations. Further, an entirely asynchronous PD, if proven as effective as other modes, stands out as the most resource-efficient choice, offering heightened convenience for all participants involved.

Yet, the success of any PD models depends, in part, on the participants' readiness and their ability to adapt to new competencies (Adnan, 2018). The objective of PD is to enrich teachers' knowledge and bolster their beliefs in their own abilities—referred to as self-efficacy (Bandura, 2008). Teacher self-efficacy (TSE) has a positive correlation with the quality of classroom instruction, and student achievement (Li et al., 2022; Schmid et al., 2023). When it comes to complex concepts like coding and CT, there is a distinct need for focused training to increase teachers' knowledge and self-efficacy. A study by Rich et al. (2021) discovered that TSE increased only for specific concepts, not others covered in a PD. Additionally, Mason and Rich (2019) identified that teachers learning coding during PD also had to acquire supporting teaching practices and pedagogical techniques.

TSE is rooted in teachers' perception of skills, knowledge, and past experiences (Bandura, 2008). It is, thus, imperative to consider teachers' pre-existing knowledge and experience, as these factors will influence their gleanings from the PD. A widely recognized phenomenon is the compensatory trajectory of development, observed when individuals starting at a lower expertise level eventually reach the proficiency level of those who start at a more advanced stage (Leppänen et al., 2004). Conversely, the Matthew effect posits that proficient learners tend to improve at an accelerated rate over time compared to their relatively lower-ability counterparts (Walberg & Tsai, 1983).

## RESEARCH AIMS AND QUESTIONS

In evaluating the effectiveness of various virtual modalities (synchronous and asynchronous) in improving competency and self-efficacy within the specific PD context for early childhood educators in the field of CS, there exists a notable research gap. This chapter delves into whether a fully asynchronous PD approach designed for both in-service and pre-service teachers, when compared to an equivalent model in a synchronous format, produces distinct outcomes in teachers' coding skills development and self-efficacy. Further, this chapter investigates whether the observed increase in self-efficacy predicts growth in teachers' coding skills and/or serves as a mediating factor in the relationship between teachers' coding skills and various influencing factors. The guiding research questions and hypotheses are:

**RQ1.** How does participation in a fully asynchronous professional development (PD) approach compared to a synchronous format influence the coding skills development of both in-service and pre-service early childhood educators?

**$H_0$:** There will be no significant difference in coding skills improvement between early childhood educators participating in a fully asynchronous PD approach and those in a synchronous format.

**RQ2.** Does an increase in self-efficacy predict growth in coding skills among early childhood educators?

**$H_0$:** There will be no significant correlation between changes in self-efficacy and growth in coding skills among early childhood educators.

The significance of this exploration lies in its potential impact on the allocation of resources for PD. If a virtual, asynchronous approach proves equally effective as other methods, it could pave the way for its broader adoption as a standard practice in teacher training.

## METHODS

To compare synchronous and asynchronous PD models, we draw insights from a randomized controlled trial conducted with in-service teachers, specifically targeting the development of coding and CT skills in K-2 students. This two-year trial (2021-2023) involved 120 teachers from U.S. public schools, assigned to the synchronous PD model. Additionally, insights are drawn from a PD program with 35 pre-service teachers who voluntarily underwent similar training but in a completely asynchronous format.

Within the synchronous model, 67 teachers received training in the "Sync-Expert" model during the first year of the trial. This model consisted of two two-hour synchronous Zoom sessions led by an experienced trainer. In the subsequent year, those trained in the first year assumed the role of Tech Leaders, leading the "Sync-Tech Leader" model—a dynamic and sustainable approach promoting continuity and effectiveness in PD. Sessions in this model lasted from four to six hours, allowing for extra time for support, logistics, and networking. In parallel, the 35 pre-service teachers followed a four-hour asynchronous model in the second year, offering flexibility aligned with their individual interests.

The three virtual PD models were designed with key effective PD characteristics, including content focus, active learning, collective participation, duration, and coherence (Avalos, 2011; Darling-Hammond et al., 2017; Desimone, 2009; Guskey & Yoon, 2009; Odden & Picus, 2014). Refer to Table 1 for the PD agenda and Table 2 for the demographic information of the study sample.

*Table 1. The CAL curriculum synchronous and asynchronous training agenda*

| Activity | Duration | Zoom (Facilitator-Guided) | Asynchronous (Self-guided) |
|---|---|---|---|
| **Part 1: Programming with ScratchJr** | | | |
| Introductions | 20 min | Participants and PD facilitators greet one another. | NA |
| Let's Learn About You | 10 min | NA | Pre-survey including demographic questions and questions gauging participant's self-efficacy, confidence, and beliefs. |
| Course Overview | 2 min | NA | Participants get introduced to the topics that will be covered in the online course and get oriented to the structure of the course website. |
| Intro to ScratchJr | 10 min | Participants learn about the history of ScratchJr and see a variety of projects that can be created using the block-based programming language. | |
| Guided Explorations | 30 min | Participants engage in a hands-on ScratchJr exploration using their own devices. The exploration activities are interspersed with formative "check for understanding" questions. | |
| Brief Break | 5 min+ | - | |
| Advanced ScratchJr | 15 min | Participants learn about advanced ScratchJr features, such as sending and receiving messages, inserting pictures, and parallel programming. | Participants learn about advanced ScratchJr features, such as how to delete characters and pages, how to initialize, copy and paste, and parallel programming. |

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*Table 1. Continued*

| Activity | Duration | Zoom (Facilitator-Guided) | Asynchronous (Self-guided) |
|---|---|---|---|
| Create a ScratchJr Project | 20 min | Participants listen to a children's book read-aloud and recreate the story using ScratchJr. | Participants are instructed to create their own ScratchJr project, given 3 different ideas for projects. |
| Share Projects | 15 min | Participants share their ScratchJr projects with others and practice sending their projects by email. | Participants are encouraged to share their project with family or friends or on social media. |
| Closing | 5 min | Q&A | Participants are provided with links to more information and resources on ScratchJr. |
| **Part 2· The CAL-ScratchJr Curriculum (The Pedagogy)** | | | |
| Four Powerful Metaphors | 30 min | Participants learn and reflect on four metaphors used as guiding frameworks for teaching coding in early childhood: coding as a playground, coding as another language, coding as a bridge, and coding as a palette of virtues (Author, 2018, 2019, 2022). | Participants learn and reflect on four metaphors used as guiding frameworks for teaching coding in early childhood: coding as a playground, coding as another language, coding as a bridge, and coding as a palette of virtues (Author, 2018, 2019, 2022). "Check for understanding" questions and reflection questions are interspersed. |
| Show What You Know | 5 min | NA | Participants are prompted to answer questions assessing their level of understanding of ScratchJr and encouraged to explore more resources. |
| Intro to CAL-ScratchJr | 30 min | Participants are introduced to the CAL-ScratchJr curriculum, its overall scope and sequence, and sample lesson activities. | |
| Brief Break | 5 min+ | - | |
| Lesson Deep-Dive | 15 min | Participants explore one lesson from their grade-level unit and reflect on how they would implement the lesson in their respective classrooms. | |
| Reflection | 15 min | Participants share their reflections with others and discuss their ideas about curriculum implementation. | NA |
| Research Study | 15 min | Participants learn about prior research conducted on the CAL-ScratchJr curriculum and how they can contribute to future research. | NA |
| Closing | 10 min | Q&A | Participants answer the post-survey, with questions gauging their self-efficacy, beliefs, concerns, and course feedback. |

*Table 2. Frequency table for nominal variables*

| Variable | *n* | % |
|---|---|---|
| Background in STEM | | |

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*Table 2. Continued*

| **Variable** | *n* | % |
|---|---|---|
| No | 91 | 68.94 |
| Yes | 25 | 18.94 |
| Unknown | 16 | 12.12 |
| Previous Coding Experience | | |
| Yes | 52 | 39.39 |
| No | 79 | 59.85 |
| Unknown | 1 | 0.76 |
| Previous ScratchJr Experience | | |
| No | 88 | 66.67 |
| Yes | 43 | 32.58 |
| Unknown | 1 | 0.76 |
| Race/Ethnicity | | |
| Mixed | 5 | 3.70 |
| White/Caucasian | 105 | 77.78 |
| Unknown | 4 | 2.96 |
| Hispanic/Latino | 8 | 5.93 |
| Black/African American | 8 | 5.93 |
| Asian | 4 | 2.96 |
| Prefer not to say | 1 | 0.74 |
| Gender | | |
| Female | 121 | 89.63 |
| Male | 9 | 6.67 |
| Prefer not to say | 5 | 3.70 |
| Model | | |
| Synchronous (Expert) | 67 | 49.63 |
| Synchronous (TechLeader) | 53 | 39.26 |
| Asynchronous | 15 | 11.11 |
| Modality | | |
| Synchronous | 120 | 88.89 |
| Asynchronous | 15 | 11.11 |

*Note.* Due to rounding errors, percentages may not equal 100%.

To assess the impact of the three PD models, teachers participated in a pre- and post-training survey. This survey aimed to gather demographic information and measure changes in teachers perceived self-efficacy after the PD training. The survey comprised seven items adapted from computing self-efficacy items developed by Rich and colleagues (2017), using a 5-point Likert-type scale, ranging from "Strongly agree" (5 points) to "Strongly disagree" (1 point). Refer to Table 3 in the next section for the list of survey items. Additionally, the validated Coding Stages Assessment (CSA; de Ruiter & Author, 2021) was administered before and after the training to evaluate teachers' growth in coding skills.

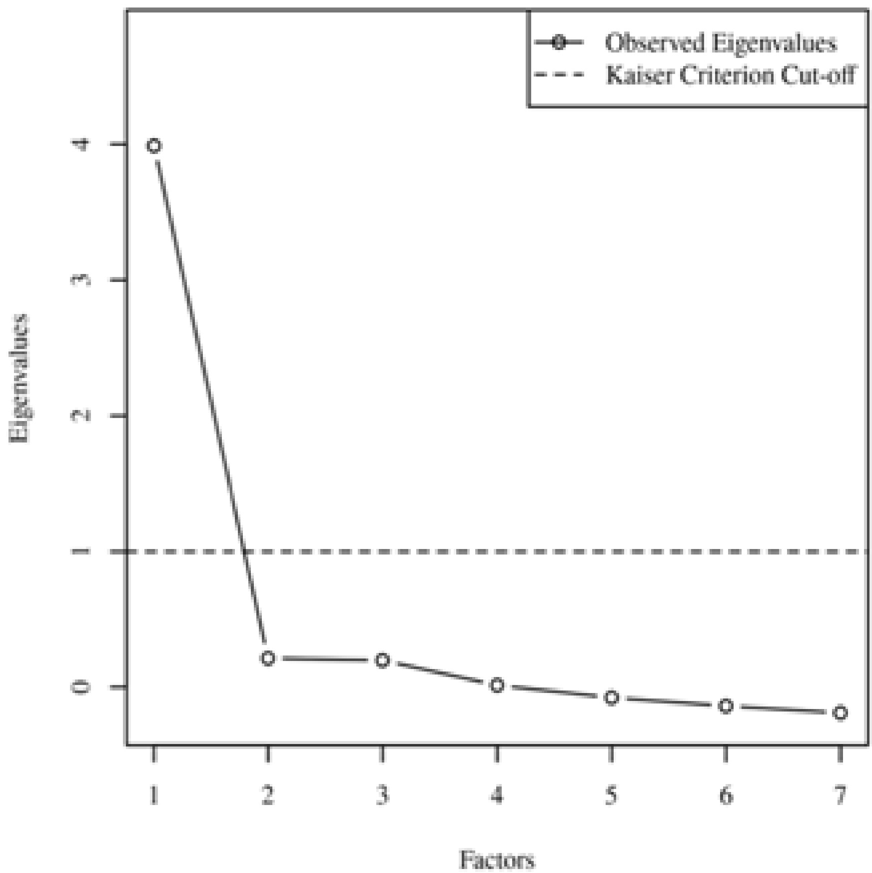
## ANALYSIS

The initial phase of our analysis centered on validating the self-efficacy scale. Using a factor analysis with Promax rotation, we employed the Kaiser criterion to ensure the items aligned with a single underlying factor. The data's normal distribution and suitable correlation coefficients supported the factor analysis (Tabachnick & Fidell, 2019). The participant-to-item ratio of 18 to 1 with a sample size of 132 suggested reliability (Costello & Osborne, 2005). The scree plot and Kaiser criterion affirmed a single underlying factor with an eigenvalue greater than one, validating the self-efficacy scale (see Figure 1).

We then created mean composite scores for pre- and post-CSA and self-efficacy and calculated the mean difference scores before integrating them into a path model. This model aimed to investigate the impact of the three virtual PD models on teachers' self-efficacy and coding growth, considering variables like teaching experience, coding and STEM background, gender, and race/ethnicity. Our analysis also delved into the mediation role of self-efficacy growth in the relationship between background variables and CSA growth. Anticipating direct impacts of PD modalities, teaching and coding backgrounds, gender, and race on both CSA and self-efficacy, we explored the indirect influence through self-efficacy.

Bootstrapping with a maximum of 100 iterations was employed for standard errors. Mahalanobis distances identified no outliers, and the determinant for the correlation matrix value of 0.55 indicated no multicollinearity (Field, 2017; Kline, 2016). Model fit was assessed using Chi-square goodness of fit, RMSEA, CFI, TLI, and SRMR (Hooper et al., 2008).

*Figure 1. Scree plot with the Kaiser criterion*




## RESULTS

The factor analysis for the self-efficacy scale revealed that the one-factor model explained approximately 57% of the total variance in the data, with an eigenvalue of 3.98. Table 3 provides a summary of the factor analysis, indicating excellent loadings for all items except item 7, which demonstrated a very good loading. No variables had a low communality (< .40), and each factor displayed at least three significant loadings (> .32), confirming a robust factor structure (Costello & Osborne, 2005).

*Table 3. Factor loadings, eigenvalues, percentages of variance, and cumulative percentages from factor analysis*

| Survey Item | Factor loading | Communality |
|---|---|---|
| I can explain basic programming concepts to children (e.g., algorithms, loops, conditionals). | 0.75 | 0.57 |
| I know where to find the resources to help students learn to code. | 0.79 | 0.63 |
| I can find applications for coding that are relevant for students. | 0.84 | 0.71 |
| I can teach ScratchJr to children. | 0.70 | 0.49 |
| I can help students debug their code. | 0.74 | 0.55 |
| I can plan out the logic for a computer program even if I don't know the specific programming language. | 0.72 | 0.52 |
| I can integrate coding into my current curriculum. | 0.71 | 0.50 |
| | **Eigenvalue** | **% of variance** |
| | 3.98 | 56.88 |

*Note*: $\chi^2(14) = 54.85$, $p < .001$.

Table 4 presents summary statistics for CSA and self-efficacy scores categorized by model in the professional development program. Notably, the differences in means from pre- to post-PD in CSA and self-efficacy scores illustrate the extent of improvement within each model and highlight their varied impact on participants' coding skills and their perceived self-efficacy.

*Table 4. Summary statistics table for pre- and post-PD CSA and self-efficacy scores by PD model*

| Variable | *M* | *SD* | *n* | $SE_M$ | Min | Max | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| CSA | | | | | | | | |
| ***Pre-PD*** | 13.22 | 9.83 | 135 | 0.85 | 2.20 | 39.00 | 1.18 | 0.38 |
| Synchronous (Expert) | 15.58 | 10.91 | 67 | 1.33 | 2.20 | 39.00 | 0.74 | -0.71 |
| Synchronous (Tech Leader) | 11.06 | 8.69 | 53 | 1.19 | 2.20 | 37.60 | 1.66 | 2.33 |
| Asynchronous | 10.34 | 5.46 | 15 | 1.41 | 4.40 | 26.40 | 1.66 | 3.14 |
| ***Post-PD*** | 25.54 | 9.69 | 135 | 0.83 | 9.30 | 39.00 | -0.26 | -1.33 |
| Synchronous (Expert) | 27.29 | 9.23 | 67 | 1.13 | 9.30 | 39.00 | -0.45 | -1.00 |
| Synchronous (Tech Leader) | 24.85 | 9.75 | 53 | 1.34 | 10.50 | 39.00 | -0.18 | -1.42 |
| Asynchronous | 20.11 | 9.76 | 15 | 2.52 | 10.20 | 33.60 | 0.33 | -1.75 |
| Self-efficacy | | | | | | | | |
| ***Pre-PD*** | 2.69 | 1.02 | 134 | 0.09 | 1.00 | 5.00 | 0.21 | -0.71 |
| Synchronous (Expert) | 2.86 | 1.09 | 67 | 0.13 | 1.00 | 5.00 | 0.12 | -0.75 |

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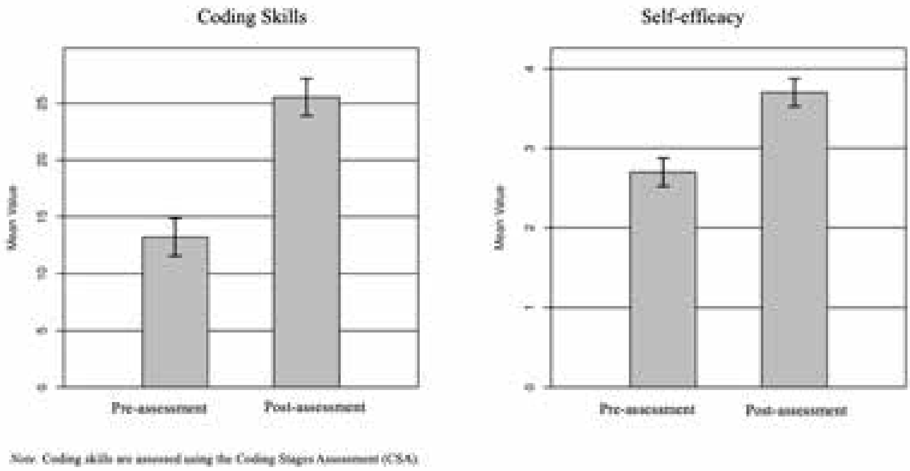
*Table 4. Continued*

| **Variable** | *M* | *SD* | *n* | $SE_M$ | **Min** | **Max** | **Skewness** | **Kurtosis** |
|---|---|---|---|---|---|---|---|---|
| Synchronous (Tech Leader) | 2.68 | 0.93 | 53 | 0.13 | 1.00 | 4.43 | -0.03 | -0.88 |
| Asynchronous | 1.96 | 0.72 | 14 | 0.19 | 1.00 | 3.71 | 0.91 | 0.67 |
| ***Post-PD*** | 3.68 | 1.04 | 132 | 0.09 | 0.00 | 5.00 | -1.54 | 2.04 |
| Synchronous (Expert) | 4.01 | 0.70 | 67 | 0.09 | 1.29 | 5.00 | -1.22 | 2.38 |
| Synchronous (Tech Leader) | 3.80 | 0.67 | 53 | 0.09 | 1.00 | 4.71 | -1.43 | 4.21 |
| Asynchronous | 1.26 | 0.91 | 12 | 0.26 | 0.00 | 3.43 | 1.42 | 1.29 |

Two-tailed paired samples *t*-tests assessed the significance of mean differences between pre- and post-PD scores. The *t*-test results highlight significant growth after PD trainings in both self-efficacy with an average growth of about 12 points, $t(130) = -10.91$, $p < .001$, and CSA with an average growth of 1 point, $t(134) = -15.53$, $p < .001$, as can be seen in Figure 2. The synchronous model taught by a Tech Leader showed the highest CSA score difference (average growth of about 14 points), followed by the expert-led model (about 12 points) and the asynchronous model (about 8 points).

In terms of self-efficacy, the Expert-led model, $t(66) = -9.41$, $p < .001$, $d = 1.15$, and the Tech Leader, $t(52) = -10.21$, $p < .001$, $d = 1.40$, synchronous models demonstrated similar growth (about 1.15 and 1.12 points respectively). Interestingly, the asynchronous model displayed a nonsignificant slight decrease in self-efficacy scores of 0.70 points, $t(10) = 1.38$, $p = .196$, $d = 0.42$. To assess overall mean differences between synchronous and asynchronous models, a two-tailed independent samples *t*-test was conducted for CSA, showing non-significance, $t(133) = 1.14$, $p = .257$. However, for self-efficacy, the *t*-test yielded a significant result, $t(129) = 5.57$, $p < .001$, $d = 1.52$, indicating a significant difference in mean self-efficacy growth between the two models, with the synchronous models outperforming the asynchronous one.

*Figure 2. The means of pre- and post-coding stages assessment and self-efficacy with 95.00% CI error bars*




The path analysis results, as depicted in Table 5 and Figure 3, indicated a good fit to the data, supported by the non-significant Chi-square goodness of fit test, $\chi^2(19) = 20.20$, $p = .383$. All fit indices, as presented in Table 5 consistently indicated an adequate model fit (Hooper et al., 2008). Based on the analysis results, only prior experience with coding and ScratchJr showed a significant, albeit a negative, correlation with self-efficacy. Teachers who had prior coding or ScratchJr experience demonstrated a slower rate of growth in self-efficacy levels compared to those without coding experience.

As for mediation, there is no evidence of either partial or full mediation by Self-efficacy Growth in the relationships being examined between the independent variables (Previous ScratchJr Experience and Coding, STEM Background, Years of Teaching, Race/Ethnicity, Gender as well as the PD Model) and CSA Growth. The direct effects between the independent variables and CSA Growth were not significant in each case, indicating that full mediation by Self-efficacy might have occurred.

However, when examining the indirect effects of Self- efficacy Growth on the relationship between each independent variable and CSA Growth, none of the indirect effects were found to be significant. This suggests that a one-unit increase in each independent variable, based on its effect on Self-efficacy Growth, does not have a significant impact on CSA Growth. Moreover, the total effects of each independent variable on CSA Growth were not significant. This indicates that a one-unit increase in each independent variable does not have a significant direct effect on CSA Growth.

*Table 5. Unstandardized loadings (standard errors), standardized loadings, and significance levels for each parameter in the path analysis model (N = 116)*

| Parameter Estimate | Unstandardized | Standardized | *p* |
|---|---|---|---|
| **Regressions**<br>**Self-efficacy Growth** | | | |
| PD Model | -0.16(0.13) | -0.08 | .241 |
| Race/Ethnicity | -0.06(0.09) | -0.07 | .527 |
| Years of Teaching Experience | 0.002(0.006) | 0.02 | .761 |
| STEM Background | 0.13(0.20) | 0.06 | .514 |
| Previous Coding Experience | -0.50(0.19) | -0.27 | .009 |
| Previous ScratchJr Experience | -0.56(0.18) | -0.28 | .002 |
| Gender | 0.14(0.17) | 0.04 | .424 |
| **CSA Growth** | | | |
| Previous ScratchJr Experience | -2.52(2.33) | -0.13 | .280 |
| Previous Coding Experience | -0.93(1.73) | -0.05 | .594 |
| STEM Background | 0.04(2.12) | 0.002 | .985 |
| Years of Teaching Experience | -0.03(0.09) | -0.03 | .762 |
| Race/Ethnicity | -0.71(1.00) | -0.08 | .479 |
| PD Model | 1.71(2.00) | 0.09 | .393 |
| Gender | 5.38(3.11) | 0.14 | .084 |
| Self-efficacy Growth | 0.55(1.08) | 0.06 | .612 |
| Indirect Effect of CSA Growth on Previous ScratchJr Experience by Self-efficacy Growth | -0.31(0.61) | -0.02 | .610 |
| Total Effect of CSA Growth on Previous ScratchJr Experience | -2.82(2.14) | -0.14 | .188 |
| Indirect Effect of CSA Growth on Previous Coding Experience by Self-efficacy Growth | -0.28(0.66) | -0.02 | .677 |
| Total Effect of CSA Growth on Previous Coding Experience | -1.20(1.62) | -0.07 | .460 |
| Indirect Effect of CSA Growth on STEM Background by Self-efficacy Growth | 0.07(0.27) | 0.003 | .791 |
| Total Effect of CSA Growth on STEM Background | 0.11(2.12) | 0.005 | .959 |
| Indirect Effect of CSA Growth on Years of Teaching Experience by Self-efficacy Growth | 0.001(0.007) | 0.001 | .874 |
| Total Effect of CSA Growth on Years of Teaching Experience | -0.03(0.09) | -0.03 | .772 |
| Indirect Effect of CSA Growth on Race/Ethnicity by Self-efficacy Growth | -0.03(0.13) | -0.004 | .801 |
| Total Effect of CSA Growth on Race/Ethnicity | -0.74(1.00) | -0.08 | .459 |
| Indirect Effect of CSA Growth on PD Model by Self-efficacy Growth | -0.09(0.24) | -0.005 | .717 |
| Total Effect of CSA Growth on PD Model | 1.62(2.01) | 0.09 | .421 |

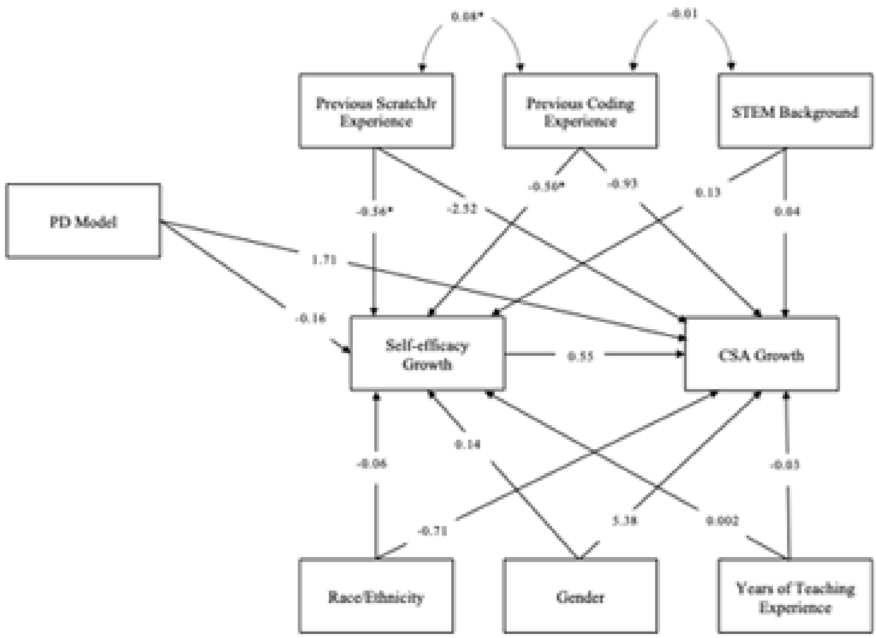
continued on following page

*Table 5. Continued*

| **Parameter Estimate** | **Unstandardized** | **Standardized** | *p* |
|---|---|---|---|
| Indirect Effect of CSA Growth on Gender by Self-efficacy Growth | 0.08(0.22) | 0.002 | .726 |
| Total Effect of CSA Growth on Gender | 5.46(3.16) | 0.14 | .084 |
| **Covariances** | | | |
| Covariance for STEM Background and Previous Coding Experience | -0.01(0.02) | -0.07 | .396 |
| Covariance for Previous Coding Experience and Previous ScratchJr Experience | 0.08(0.02) | 0.34 | < .001 |
| **Errors** | | | |
| Error in Previous ScratchJr Experience | 0.21(0.02) | 1.00 | < .001 |
| Error in Previous Coding Experience | 0.25(0.006) | 1.00 | < .001 |
| Error in STEM Background | 0.17(0.02) | 1.00 | < .001 |
| Error in Years of Teaching Experience | 101.73(12.86) | 1.00 | < .001 |
| Error in Race/Ethnicity | 1.06(0.26) | 1.00 | < .001 |
| Error in PD Model | 0.24(0.009) | 1.00 | < .001 |
| Error in Gender | 0.06(0.02) | 1.00 | .003 |
| Error in Self-efficacy Growth | 0.67(0.10) | 0.78 | < .001 |
| Error in CSA Growth | 77.78(8.89) | 0.93 | < .001 |

*Note.* $\chi^2(19) = 20.20$, $p = .383$; TLI = 0.93; CFI = 0.97; RMSEA = 0.02, 90% $CI = [0.00, 0.09]$; SRMR = 0.06; -- indicates the test was not conducted as the observed variance/covariance values were used.

*Figure 3. Results of the path analysis model*




## DISCUSSION

Our study was designed to assess the efficacy of virtual PD models in enhancing the competency and self-efficacy of early childhood educators in the field of CS, addressing a significant research gap. The primary objective was to investigate whether a fully asynchronous PD approach, when compared to an equivalent synchronous model, yields comparable outcomes in teachers' coding skills development and self-efficacy. Additionally, this chapter explored whether the increase in self-efficacy serves as a predictor for the growth in teachers' coding skills and/or functions as a mediating factor in the relationship between teachers' coding skills and various influencing factors.

Consistent with established research (Jin & Harron, 2023; Kapoor et al., 2023; Mouza et al., 2022; Polly, 2015), both pre- and in-service teachers exhibited significant growth in both coding skills and self-efficacy, regardless of the PD approach. The comparison between synchronous and asynchronous models revealed that teachers demonstrated similar growth in coding skills (CSA) irrespective of the virtual delivery approach, aligning with findings from Chen and Cao (2022) and Lawrence and Ogundolire (2022). The significance of this exploration lies in its potential impact on resource allocation for PD, as all three approaches prove equally effective in enhancing teachers' competency. This supports the notion of adopting virtual approaches as a standard practice in teacher training. Notably, the asynchronous model's standout feature was its flexibility, offering a personalized learning experience that aligns with the pace and preferences of individual learners, free from temporal and geographical constraints.

While CSA scores did not significantly differ between synchronous and asynchronous models, a notable distinction emerged in self-efficacy growth, with synchronous models outperforming asynchronous ones. The synchronous models, characterized by real-time interaction and engagement, appeared to contribute more effectively to the enhancement of self-efficacy compared to the more flexible but less interactive asynchronous model. This finding aligns with prior research indicating that teacher self-efficacy tends to grow more when part of a group compared to individual feedback (Goode et al., 2020; Sun et al., 2023, 2023; Zheng et al., 2019). Marchisio et al. (2018) emphasized the significant role of online asynchronous collaboration, highlighting its contribution to enhancing teacher professional knowledge and competencies. This insight can be invaluable for educators and professionals involved in designing teacher training programs, encouraging exploration of online asynchronous collaboration to optimize the impact of such programs.

Within the synchronous model, the choice of facilitator played a crucial role, with the Tech Leader-led model showing the highest CSA score difference, underscoring the impact of peer expertise in enhancing coding skills. This aligns with previous research suggesting that PD facilitated by a trained and trusted colleague can be particularly effective (Hassler et al., 2018). Conversely, the expert-led model demonstrated the most substantial self-efficacy growth, consistent with prior research emphasizing the influential role of expert guidance in shaping educators' self-efficacy (Jin & Harron, 2023; Kapoor et al., 2023; Mouza et al., 2022).

The exploration of factors predicting CSA and self-efficacy growth provided nuanced insights. Educators with prior coding or/and ScratchJr experience exhibited a significant increase in overall self-efficacy levels. However, educators with coding experience demonstrated an increase in self-efficacy, but this growth occurred at a rate that suggests a compensatory pattern, possibly influenced by the existing proficiency in coding (Leppänen et al., 2004). This nuanced aspect adds depth to our understanding, indicating that the impact of coding experience on self-efficacy growth may be different from the trajectories observed in those without such experience.

Contrary to expectations, mediation analyses did not support the notion of full mediation. This outcome suggests that the observed increase in self-efficacy resulting from training did not entirely account for CSA growth or mediate the influence of other factors. This implies that factors beyond self-efficacy contribute to the complex landscape of CSA growth among educators. These findings prompt a deeper exploration into the dynamics at play within the realm of professional development and its diverse impacts on early childhood educators' competency in teaching CS concepts and their self-efficacy.

Several implications and recommendations emerge from our study, shedding light on key considerations for future training and research in the field of early childhood education:

The comparable outcomes observed between synchronous and asynchronous virtual PD models, fostering substantial growth in coding skills and self-efficacy among early childhood educators, propose an efficient allocation of resources. This suggests advocating for the adoption of virtual approaches as a standard practice in teacher training. Recognizing the nuanced impact of prior coding or ScratchJr experience on educators' self-efficacy levels underscores the importance of tailoring training programs to address the compensatory pattern observed among educators with coding experience. Future training initiatives can capitalize on the flexibility of asynchronous models to offer a personalized learning experience aligned with individual learners' pace and preferences.

However, acknowledging the impact of real-time interaction on self-efficacy is essential. Strategizing ways to optimize asynchronous models for enhanced self-efficacy outcomes becomes a key consideration. Online asynchronous collaboration, as highlighted by Marchisio et al. (2018), can contribute to enhancing teacher professional knowledge and competencies. Encouraging exploration of this approach in designing teacher training programs may yield valuable insights. Moreover, recognizing the significant role of facilitators within synchronous models emphasizes the potential of incorporating peer expertise in facilitation roles. Simultaneously, appointing experts to support these facilitators can enhance the overall impact on educators' self-efficacy. while also appointing experts to support them to maximize the impact on educators' self-efficacy.

In terms of future research, our study suggests that factors beyond ones explored here contribute to educators' competency. Therefore, a deeper exploration into the dynamics within the realm of PD, considering its diverse impacts on early childhood educators' competency in teaching CS concepts and their self-efficacy, should be a focus. This exploration may involve delving into the roles of contextual factors and individual differences in shaping outcomes.

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## KEY TERMS AND DEFINITIONS

**Asynchronous Learning:** A learning modality that is online and self-paced, without a live facilitator or peers.

**Coding Competence:** One's proficiency in understanding and writing code in a specific language.

**Computational thinking:** The underlying cognitive processes that support problem solving in relation to computers.

**Pedagogy:** A certain framework, method, or practice for teaching.

**Professional Development:** Learning opportunities for one to advance their expertise in a certain area.

**Programming:** The process of writing in a language that a computer can interpret.

**Self-efficacy:** One's belief in their own ability to complete a task or reach a goal.

**Synchronous Learning:** A learning modality that involves a live online session with a facilitator and peers present.