High School Teachers' Self-efficacy in Teaching Computer Science

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Self-efficacy is an important construct for CS teachers' professional development, because it can predict both teaching behaviors as well as student outcomes. Research has shown that teachers' self-efficacy can be as influential as their actual level of knowledge and abilities. However, there has been very limited research on CS teachers' self-efficacy. This study describes the development and implementation of an instrument that measures secondary school teachers' self-efficacy in teaching computer science. Teachers attended a nine-week hybrid professional development program and completed the computer science teaching self-efficacy instrument. Confirmatory factor analysis validated the self-efficacy instrument, which can be potentially used in other CS education settings. The results also indicated that teachers' self-efficacy in the content knowledge and pedagogical content knowledge dimensions of teaching computer science significantly increased from participating in the professional development program.

CCS Concepts: • **Social and professional topics → Computer science education**; **K-12 education**; Accreditation;

Additional Key Words and Phrases: Self-efficacy, distributed learning environments, secondary education, computer science education, computer science teacher education

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1 INTRODUCTION

Computer science (CS) education in secondary schools is essential to the CS education pipeline and promotes such fundamental skills as computational thinking [1, 35, 50, 79, 81]. Recently, several evidence-based CS curricula (e.g., Exploring Computer Science, AP Computer Science Principles) have been developed and widely adopted in secondary schools around the nation to broaden participation and inspire interest in CS classrooms [31, 54]. However, despite the exponential increase in secondary school CS class enrollment, well-prepared CS teachers are in shortage for the fast-growing demand [43, 59].

Furthermore, because CS content is challenging in nature and creating equitable learning environments for diverse students is innately complex, the effective implementation of CS curriculum is contingent upon teachers' high level of self-efficacy in pedagogical and content knowledge [32, 48]. Research in other STEM disciplines has shown that teachers' self-efficacy is as important as teachers' actual knowledge and skills [74]. Currently, the limited research in the field has examined teacher self-efficacy in using computational thinking as a ubiquitous mindset for problem-solving across all disciplines [11, 81] or in using technology tools to implement digital competencies [60]. However, there has been a dearth of research on teachers' self-efficacy in teaching CS in secondary schools [52, 59]. Additionally, research on using hybrid structures (i.e., online and face-to-face components) that allow in-service teachers to engage in high-quality professional development (PD) over extended duration has been very limited [28]. In this study, we designed a measurement tool to examine high school teachers' self-efficacy in teaching computer science and used the measurement tool to explore changes in teachers' self-efficacy during a hybrid PD program.

The following research questions are investigated in this study:

1. What are the validity and reliability of the self-efficacy survey developed for secondary school CS teachers?
2. What are the changes in teacher self-efficacy from attending a CS teacher PD course as shown by the self-efficacy survey?

2 BACKGROUND

Over the past decade, under national initiatives such as CS10K [15], a variety of evidence-based CS curricula have been developed to engage students from diverse backgrounds in CS classrooms [2]. Despite such progress, there has been a lack of well-prepared CS teachers who can effectively teach CS content and adequately address equity issues in CS classrooms [32]. Thus, recent research on CS education has highlighted the importance of preparing teachers with CS content knowledge and equitable pedagogical practices [32]. This study examines teachers' self-efficacy in the subject matter and pedagogical content knowledge for teaching CS, which can provide critical insights for structuring the much-needed CS teacher education programs. In fact, this study is part of a project developing a CS teacher certificate program consisting of four courses to prepare in-service teachers to teach CS.

2.1 Self-efficacy of Computer Science Teachers

2.1.1 The Role of Self-efficacy in CS Teacher Development. Self-efficacy has important roles in CS teachers' PD, because it can predict both teaching behaviors, such as engagement and persistence [71, 72], as well as student outcomes, such as motivation and academic performance [41, 48, 82]. According to the social cognitive theory [5, 7, 69], self-efficacy impacts teacher behaviors through the triadic reciprocal determinism framework, involving personal (e.g., beliefs and expectations), behavioral (e.g., efforts and actions), and environmental factors (e.g., social context). Thus, self-efficacy can influence the actions that teachers choose to take in the face of impediments by shaping their interpretations of challenges [6, 9]. For example, teachers with a high level of self-efficacy tend to interpret challenges as opportunities for growth and are willing to enact sustained efforts, whereas teachers with a low level of self-efficacy tend to perceive challenges as indicators of insufficient abilities and may give up early to avoid threats to personal competence [7]. Thus, self-efficacy is particularly important for CS teacher education, because CS as a discipline requires high level of effort expenditure and tenacity: Problem-solving processes depend on numerous iterations and CS concepts are known to be challenging [36, 58]. In addition, teachers' self-efficacy in CS can provide modeling and shape students' self-efficacy in this challenging discipline [64]. Despite its importance, the research on CS teachers' self-efficacy has been lacking [59]. We therefore draw on the research from other fields to inform the framework for the current study.

2.1.2 Measuring CS Teachers' Self-efficacy. Self-efficacy concerns one's judgments about their "capabilities to organize and execute courses of action required to attain designated types of performance" [5, p. 391]. As a psychological construct, self-efficacy measures the extent to which one believes that one can successfully perform a task in a specific situation [10]. In the context of teacher self-efficacy, one strand of research has examined this construct in the form of outcome expectancy—teachers' belief in the extent to which their teaching practices can impact student learning [47]. In comparison, another strand of research focuses more on efficacious beliefs about behaviors—teachers' beliefs in their ability to complete certain tasks in teaching [8, 48]. These differences in theoretical frameworks have resulted in variances in the construction of teacher self-efficacy measurement tools. However, recent literature has suggested adhering to the original definition of self-efficacy—one's belief in the ability to successfully accomplish a task in a specific area [5, 48, 61].

Previous research has also cautioned that self-efficacy is content-specific, where narrowly defined tasks are more predictive of future behaviors than those covering a broad spectrum [41, 48]. Regarding domain specificity, Bandura [8] has suggested that researchers identify the key elements needed to function in a domain and construct self-efficacy items to assess the relevant elements. However, the items should avoid being either overly specific or highly general, and the level of specificity should depend on the purpose of the research [75]. The domain-specific teacher self-efficacy surveys reported in previous research generally measure teachers' instruction in a specific domain and their sense of efficacy as a teacher in general. For example, Tschannen-Moran and Johnson [75] measured literacy teachers' self-efficacy by creating a Teachers' Sense of Efficacy for Literacy Instruction (TSELI) survey and a Teacher Sense of Efficacy Scale (TSES). To create the items for the TSELI, the researchers referred to the NCTE/IRA standards for English Language Arts and the IRA Standards for Reading Professionals, and the items focused on teachers' self-efficacy in using teaching strategies to help students acquire the specific literacy skills identified in the Standards. The TSES measures the teachers' general teaching efficacy, such as instructional strategies, student engagement, and classroom management.

Although this line of research primarily focused on teachers' self-efficacy in using pedagogical strategies in teaching [41, 48, 75], for CS teachers it is important to also assess their self-efficacy in accomplishing tasks in the content domain. As Menekse [59] pointed out, CS teacher education is unique compared to other disciplines in that teachers generally have limited prior exposures to CS content. Thus, to construct self-efficacy items for CS teachers, this study drew on the teacher education literature that identified the different types of content knowledge as essential to the development of teacher knowledge [48, 70] and focused on the teachers' self-efficacy in the subject matter content knowledge (CK) and pedagogical content knowledge (PCK) dimensions. Previous research has suggested that PCK—the "adaptation of subject matter knowledge for pedagogical purposes" [56, p.7]—is an important construct built upon teachers' CK and pedagogical knowledge (PK) [76]. However, because the participants are experienced in-service teachers, this study mainly focuses on teachers' self-efficacy in the CK and PCK specific to teaching CS, rather than the PK for general instructional practices. Based on the previous research on teacher knowledge and teacher self-efficacy [4, 34, 41, 48, 51, 70], the two major constructs in the self-efficacy survey are defined as follows:

- Self-efficacy in CK: Teachers' belief in their capabilities to accomplish tasks relevant to the knowledge of the CS subject and its organizing structures;
- Self-efficacy in PCK: Teachers' belief in their capabilities to apply situated teaching strategies for CS topics.

2.1.3 Promoting CS Teacher Self-efficacy. Social cognitive theory has suggested that self-efficacy can be facilitated by providing experiences that cater to the four sources of self-efficacy: (a) mastery experiences, (b) vicarious experiences, (c) physiological state, and (d) social persuasion [6, 41, 48]. Mastery experiences—the successful experiences of accomplishing content-specific tasks—have been identified as the most influential predictor for teachers' self-efficacy [74]. For example, Tschannen-Moran and Hoy [74] found that mastery experiences measured as teachers' satisfaction with past professional performances was significantly associated with the development of teachers' self-efficacy. In addition, Bandura [7] cautioned that easy success is not as beneficial as overcoming obstacles for self-efficacy: Successful mastery experiences through difficulties can foster resilient forms of self-efficacy. The CS learning activities involved in the current study have the advantages of providing mastery experiences that are only obtainable through overcoming challenges and putting forth persistent effort.

Another major source of self-efficacy is vicarious experiences—that is, the process of gaining self-efficacy through observing the success of similar social models. The similarity and the relatability of the social model to the self has been identified as a key factor in gaining self-efficacy through vicarious experiences [48]. Thus, a possible mechanism for developing teachers' self-efficacy in a CS program is through providing teachers with relatable social models in instructors and peers.

With respect to social persuasion, providing positive appraisals focused on self-improvement rather than peer comparisons has been found to increase self-efficacy [7]. Therefore, the PD program in the current study provided social persuasions focused on self-improvement by advocating growth mindset from the beginning of the course and using formative assessment to generate feedback based on growth.

Physiological state, or the perception of ones' emotional states and physiological reactions, is also an important contributor to the development of self-efficacy [5, 48]. However, we chose not to focus on this factor due to the research goals and the setup of the study, where the collection of data on emotional states and physiological reactions was not feasible.

2.2 In-service Teacher Professional Learning

Teachers who are faced with changes in their educational landscapes, such as new CS curriculum implementation, need to be adequately prepared to respond to new demands. For in-service teachers, PD programs are essential to fostering teachers' professional learning and preparing teachers to adapt to changing demands [29, 77]. Teacher participation in high-quality PD can lead to developments in teacher knowledge (e.g., CK, PCK) and teacher beliefs (e.g., self-efficacy), resulting in shifts in instructional practices and ultimately improving student performance [22].

Previous research has identified several core characteristics of high-quality PD [13, 18, 22], such as providing opportunities for active learning, affording collective participation, having a content focus, emphasizing coherence, and providing sufficient duration [22]. Although teachers' participation in PD programs that adhere to these high-quality design features do not universally translate to positive outcomes in student performance [23, 46], recent studies have identified positive associations between STEM teachers' PD participation and increases in teacher knowledge, teacher self-efficacy, adoption of instructional practices, and improvement in student learning, e.g., References [27, 30, 53, 62, 68]. For instance, Price and Chiu [62] found that science teachers increased in their self-efficacy with medium effect sizes from participating in a museum-based PD program, which adhered to five of the six high-quality PD design characteristics.

Recent developments in teacher education have called for more research on the affordance and effectiveness of hybrid PD programs [13, 20, 21], which are designed to provide teachers with content and pedagogy learning in both face-to-face and online settings. In recent studies, PD programs with online components have been found to benefit teacher development in self-efficacy, e.g., References [28, 45]. For example, Fishman et al. [28] examined 49 cluster randomized teachers participating in a PD program for a science curriculum adoption, either in an online or a face-to-face condition. The study found pre to post gains in teachers' self-efficacy of approximately a standard deviation in the online PD condition and slightly lower self-efficacy gains for teachers in the face-to-face PD activity [28]. However, there has been very limited research examining teacher self-efficacy in hybrid PD programs in the context of CS education [59]. Therefore, this current study contributes to the nascent empirical research base by examining changes in CS teachers' self-efficacy in hybrid PD programs.

2.3 Survey Validation

This current study intends to demonstrate and examine the validity and reliability of a CS teacher self-efficacy survey by conducting a confirmatory factor analysis (CFA) using the partial least squares structural equation modeling (PLS-SEM) approach. The PLS-SEM approach was chosen for its advantages over other approaches (e.g., covariance-based structural equation modeling) and its appropriateness for the purpose of this study [38–40]. The partial least squares (PLS) algorithm assumes that latent constructs can be summed up by the linear combinations of the explanatory variables [38, 57]. The algorithm applies dimension reduction to remove the multicollinearity in the explanatory variables [57]. Carrascal et al. [16] have also shown in a simulation experiment that Please was more reliable than a combination of principal component analysis and multiple regression in identifying the correlations between related variables in studies with small sample sizes. These advantages in coping with multicollinearity and having fewer restrictions on data distribution and sample size are suitable for this study, where we examined the limited sample of high school in-service teachers enrolled in our CS teacher certificate program.

3 METHODS

3.1 Participants

The participants are high school in-service teachers from a wide variety of disciplines in different schools that mainly serve underrepresented minority students in Southern California. The PD program was funded by NSF, which allowed the participants to attend the PD program free of charge and outside of their normal working hours (i.e., in the evenings and on weekends).

A total of 59 teachers responded to the pre- and post-surveys distributed in the TECS PD course. Table 1 presents the participants' demographic information.

In cohort one, 27 teachers participated in the PD course and 24 teachers responded to the surveys. In cohort two, which started one year after cohort one, 35 teachers participated in the PD course and responded to the surveys. Due to missing data and issues beyond our control (e.g., sick leaves), among the 59 participants, a total of 48 teachers completed the TECS course pre-survey and 51 teachers filled out the post surveys. We acknowledge the limited number of teacher participants in this study. However, it is important to note that the teachers in this study are enrolled as part of a first CS teacher certificate program in the state. Due to the recency of this certificate

Table 1. Participants' Demographic Information

Category	Frequency	Percent
Ethnicity		
White	30	50.85
Asian	13	22.03
Hispanic or Latino	11	18.64
Multi-ethnic	3	5.08
Native Hawaiian or Pacific Islander	1	1.69
Other	1	1.69
Gender		
Male	34	57.63
Female	25	42.37
Credentialed Subject*		
Math	25	40.32
Science	14	22.58
Technology	7	11.29
English	5	8.06
World Languages (other than English)	4	6.45
Social Sciences	2	3.23
Business	2	3.23
Engineering	1	1.61
Special Education	1	1.61
Visual and Performing Arts	1	1.61
Teaching Experience		
1–5 years	14	23.73
6–10 years	13	22.03
11–15 years	16	27.12
16–20 years	9	15.25
More than 20 years	7	11.86

*Some teachers are credentialed in more than one subject area. For each credential category, its percentage is calculated as a ratio between its frequency and the total number of credentials reported (i.e., 62 rather than 59).

program and the level of commitment this program requires—two years, four courses, totaling 16 credit hours—the recruitment and retention of teacher participants have been challenging, which resulted in limited sample size. Still, there is great value in this sample—results from this study can inform many of such certificate programs for CS teachers that are emerging around the nation.

3.2 Procedures

Both cohorts of teacher participants attended a nine-week TECS PD course. Using a hybrid format, the course consists of three six-hour face-to-face classes, weekly online synchronous classes on a video conferencing platform (i.e., Zoom) interspersed between the face-to-face classes, and online asynchronous learning modules in a learning management system (i.e., Canvas). The TECS PD course highlighted the major components of the Exploring Computer Science (ECS) curriculum: Inquiry, Equity, and CS Concepts [32]. The design of the learning activities was based on the best practices suggested by the previous research in teacher PD, CS education, and the major sources for developing teacher self-efficacy [10, 22, 32, 71]. The PD instructor is an experienced high school teacher from a non-CS background and gained the expertise through extensive participation in related CS teacher PD as well as professional learning communities. The instructor has taught the ECS curriculum for several years and has facilitated multiple TECS PD programs for high school teachers around the nation.

Consistent with the core characteristics identified in high-quality PD programs [22], our TECS PD provided *opportunities for active learning* in both the face-to-face and online learning environments. The online asynchronous modules engaged participants to write reflection essays on readings related to equity in CS education, create computing artifacts (e.g., web pages created in HTML/CSS, animation/games created in Scratch), and adapt lesson plans from the ECS curriculum. In the face-to-face classes, the participants engaged in active learning through the Teacher-Learner-Observer model, where they experienced learning and reflected on the learning processes [32]. To illustrate, during the class on "What is a computer?," the teacher participants took the roles of learners, while the PD instructor applied the best practices for promoting inquiry and equity to teach the lesson. The participants then reflected on how to promote inquiry-based learning for diverse students, facilitate hands-on activities, and create computing artifacts. There were also PD facilitators (CS education researchers and education researchers) who served as observers and provided feedback regarding the teaching and learning of the lesson. Throughout this process, the teacher participants engaged actively as learners to learn about the contents and discuss with peers, instructors, and facilitators to reflect on the lessons.

The TECS PD course also addressed the high-quality PD criteria by *affording collective participation* (e.g., by using online learning platform features to assign teachers to peer review groups to provide each other with feedback, and grouping features to facilitate collaboration on creating computing artifacts and micro-teaching demonstrations); *focusing on content* (e.g., by introducing CS concepts through online learning modules, online meetings, and face-to-face meetings); and *providing sufficient duration* (e.g., by spanning over nine weeks and totaling 30+ meeting hours and 40+ homework hours). All participants were required to attend all the sessions unless they had unexpected personal matters such as sick leave. In those rare instances, the participants were required to watch the video recording of the sessions and complete corresponding activities that would make up for the missed sessions. Additionally, all participants reported in this study passed the course and continued their way to the certification (the limited number of participants who dropped out due to personal matters such as family issues or work relocation did not complete the survey and were not reported in this study due to the focus of the research questions).

The participants took a pre- and post- self-efficacy survey, prior to and after the course. The survey was distributed online and sent to each teacher's email address. To keep the responses anonymous and at the same time connected across the pre and post surveys, a unique key was generated by the online survey system for each teacher's email address and was only accessible by external evaluators. The evaluators then helped the researchers link all the responses across time while keeping the teachers' identities anonymous.

3.3 Measures

Although this study implemented a pre-post survey design, previous research has cautioned that participants may experience response-shift bias: self-evaluation criterion may shift from pre to post survey due to the changes in knowledge after taking part in the intervention [42]. To address this issue, the retrospective pre-post approach, where participants rate their pre-intervention status based on the knowledge level after an intervention, has been implemented alongside the traditional pre-post design to mitigate the influence of response-shift bias [25, 73]. Thus, in addition to the pre-survey at the beginning of the course, the current study applied the retrospective pre-post format in the post-survey implementation: Participants rate both their self-efficacy after completing the course as well as the self-efficacy prior to taking the course based on their current understanding of the contents.

3.3.1 Self-efficacy Survey. We developed a self-efficacy survey[1] with two sub-sections that assess: (1) the teachers' self-efficacy in the content knowledge (CK) and (2) pedagogical content knowledge (PCK) of teaching CS. Following the guidelines for constructing self-efficacy surveys proposed by Bandura [8], we developed survey items that accurately reflect the construct by using the "I can [do]..." sentence structure to assess participants' perceived capabilities. The survey asked participants to rate their confidence in the ability to perform tasks on a five-point Likert scale, ranging from Strongly Disagree (point value of 1) to Strongly Agree (point value of 5). The average completion time for the self-efficacy survey is around eight minutes.

In the survey, the CK self-efficacy sub-section consists of 20 items. Because Bandura [8] highlighted that self-efficacy survey items should be content-specific and reflect the major concepts required to function in a particular domain, the current study referred to the CS domain content identified in the Praxis Computer Science Exam test specifications [26], K-12 Computer Science Framework [1], and the Computer Science Teachers Association (CSTA) K-12 Computer Science Standards (2017) [17], as well as the learning objectives of the ECS curriculum, including algorithms, programming, web design, and impact of computing. Therefore, the content knowledge items in this survey are not limited to the scope of the ECS curriculum but are also consistent with other CS education settings in secondary schools. The internal consistency of the CK self-efficacy items is Cronbach's alpha = 0.96. Sample items include:

- Algorithm: I can explain how to use sorting algorithm to solve problems.
- Web design: I can identify the major criteria for evaluating the quality of a website.
- Programming: I can use iteration in programming.
- Impact of computing: I can identify the obstacles to equal access to computing among different demographic groups.

The PCK self-efficacy sub-section consists of nine items adapted from the surveys used in previous research on teaching self-efficacy in STEM, which examined personal teaching efficacy and outcome expectancy [12]. However, recent research has recommended distinguishing outcome expectancy from teaching self-efficacy [48]. Thus, this study developed the PCK survey items by adapting the personal teaching self-efficacy surveys rather than the outcome expectancy surveys in STEM [12, 41], as well as surveys that examined teacher self-efficacy in PCK [51]. The PCK items measure teachers' self-efficacy in using pedagogical practices specific to CS instruction, such as facilitating equity practices and addressing students' understanding of CS concepts. We identified PCK items based on experienced CS teacher and researchers' input as well as the pedagogical strategies deemed important in previous CS education research [31, 32, 54, 55]. The internal consistency of the PCK items is Cronbach's alpha = 0.91. To illustrate, a sample item in the self-efficacy for the PCK construct is:

- I can use inquiry-based teaching methods to promote student learning in computer science classes.

3.4 Data Analysis

To answer the corresponding research questions, the data analysis is a multi-step process that included validating the survey as well as implementing and analyzing the survey in the context of a CS teacher PD program.

[1]The survey can be shared upon request by contacting the first author.

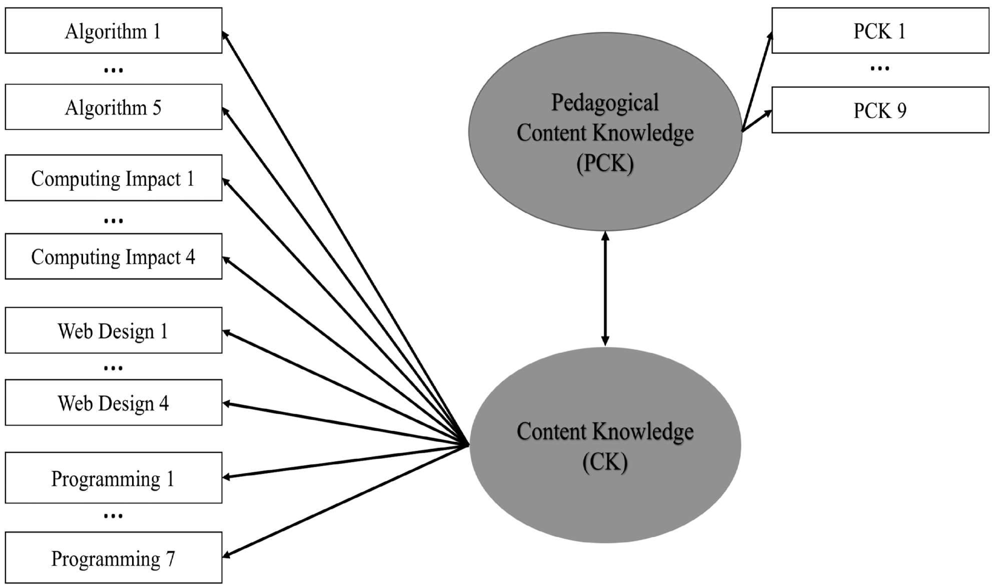

Fig. 1. The reflective measurement model for partial least squares-structural equation modeling. The arrows pointing from CK and PCK towards the survey items represent that the change in the indicators (i.e., survey items) reflect the change in the latent constructs (i.e., CK and PCK). The bi-directional arrow between CK and PCK represents the correlation between the two latent constructs.

3.4.1 Survey Validation. After the survey was constructed, we had a panel of experts examine the representativeness and the clarity of the items. The experts included high school CS teachers, CS education researchers, CS professors experienced in CS teacher preparation, and evaluation experts experienced in STEM education. Based on experts' feedback, we further revised the items to better reflect the construct of self-efficacy in the CK and PCK for CS teaching.

Subsequent to survey distribution and data collection, based on the survey validation methods proposed in previous research [38, 63], we conducted confirmatory factor analysis (CFA) using partial least squares structural equation modeling (PLS-SEM) to examine the validity and reliability of the self-efficacy survey.

As part of the CFA, we constructed a reflective measurement model based on the theories in teacher knowledge and self-efficacy [8, 70]. A reflective measurement model indicates that the change in the indicators (i.e., self-efficacy survey items) reflects the change in the latent construct (i.e., self-efficacy in CK or PCK) [38, 67]. As shown in Figure 1, the reflective measurement model examines whether the CK and PCK self-efficacy subscale items have high factor loadings under their respective latent constructs, namely, the PCK and CK constructs. High factor loadings could imply that the items measure the same construct, suggesting that the measures employed for CK and PCK are consistent with our model.

The CFA was conducted using the post-survey data rather than the pre-survey data, because the floor effect resulting from participants' limited prior experience with CS during the pre-survey could complicate survey validation.

After conducting CFA, bias corrected bootstrapping with 1K samples was performed to test the statistical significance of the PLS-SEM results [38]. The bias corrected bootstrapping method allows us to most accurately detect Type I error [78].

Following the procedures in Hair Jr et al. [38], we examined the model metrics appropriate for the reflective measurement model in this study, including convergent validity, discriminant validity, composite reliability, and the correlation between the self-efficacy in CK and PCK.

Convergent validity describes the degree to which indicators under the same theoretical construct are positively related. The indicators belonging to the same construct should converge on the construct by way of sharing a large proportion of variance. Thus, convergent validity can be assessed by the factor loadings of indicators (i.e., survey items) on the latent constructs (i.e., self-efficacy in CK and PCK). In addition, we also examined convergent validity through the average variance extracted (AVE), which is the amount of variance captured by a construct in relation to the amount of variance caused by measurement error [38].

Discriminant validity examines the extent to which a construct is distinct from other constructs in the measurement model. Highly correlated latent constructs result in multicollinearity, which undermines the statistical significance of the explanatory variables [24]. As suggested by Henseler et al. [40], we used the heterotrait-monotrait ratio of correlations (HTMT) to check the discriminant validity of the self-efficacy in the CK and PCK constructs. The HTMT is the estimation of two constructs' correlation if the measures were perfectly reliable. The HTMT has been found to be more reliable than other approaches, such as the Fornell-Larcker criterion and cross-loadings, in examining the discriminant validity of latent constructs [40]. An HTMT ratio under 0.9 would indicate that the discriminant validity of the constructs is acceptable, implying that the construct is unique [40].

Reliability. We measure the internal consistency of the measures by using the Cronbach's alpha and the composite reliability. While Cronbach's alpha has been traditionally used for establishing survey reliability, we also reported the composite reliability, which considers the outer loadings of the indicators [38]. Alternatively, it can be interpreted as an indicator of the shared variance among observed items.

3.4.2 Measuring Changes in Teacher Self-efficacy in a PD Program. Paired sample t-tests were conducted to identify the changes in teachers' self-efficacy. Due to missing data (e.g., certain participants completed the pre-survey, but failed to respond to the post-survey), the pairwise deletion approach (i.e., only matched pairs were included in the analysis) was implemented to maximize the use of the sample [33]. Prior to the paired sample t-test, we checked the normality of the change scores using the Shapiro-Wilk W Test. For self-efficacy in CK, the change score between the pre-survey and the post-survey ($W = 0.95$, $p = 0.056$) as well as the change score between the retrospective-before survey and post-survey ($W = 0.96$, $p = 0.1$) follows a normal distribution. For self-efficacy in PCK, the change score between the pre- and post-survey ($W = 0.99$, $p = 0.94$) demonstrated normality, but between the retrospective-before and post-survey the distribution was not normal ($W = 0.95$, $p = 0.03$). Thus, we used the nonparametric test, the Wilcoxon signed rank test to examine the change from the retrospective-before to the post-survey in PCK [80].

4 RESULTS

4.1 Survey Validation

There is a dearth of research on measuring teachers' self-efficacy in content and pedagogical content knowledge [66], particularly in CS education. Here, we explore the validity and reliability of the CS teachers' self-efficacy survey developed in this study.

Convergent Validity. Besides conducting expert-review of content validity as described in the Measures section, we also examined convergent validity, or the degree to which indicators (i.e., survey items) converge to assess the same construct.

Table 2. Factor Loadings and Standard Error of the Survey Items on the Two Constructs of Self-efficacy in Content Knowledge and Pedagogical Content Knowledge

Items	Factor Loading	Standard Error
Content Knowledge		
Algorithm 1: Explain connection of binary systems with computers	0.64	0.02
Algorithm 2: Explain how to use search algorithms	0.77	0.01
Algorithm 3: Explain how to solve a minimal spanning tree	0.55	0.02
Algorithm 4: Describe algorithms to meet objectives	0.80	0.01
Algorithm 5: Explain how to use sorting algorithms	0.73	0.01
Computing Impact 1: Describe how computing enables innovation	0.67	0.01
Computing Impact 3: Identify implications of unethical computing	0.42	0.02
Programming 1: Use feedback to improve object-based program	0.74	0.01
Programming 2: Use variables in programming	0.87	0.01
Programming 3: Create conditionals in programming	0.82	0.01
Programming 4: Create computer programs in block-based language	0.82	0.01
Programming 5: Create event-driven programs to respond to external events	0.75	0.01
Programming 6: Use iteration in programming	0.75	0.01
Programming 7: Create programs through pair programming	0.60	0.01
Web Design 1: Identify criteria for evaluating website quality	0.75	0.01
Web Design 2: Create a storyboard for a multi-page website	0.62	0.02
Web Design 3: Use HTML tags and CSS to separate style from structure	0.81	0.01
Web Design 4: Use HTML and CSS to create functional websites	0.84	0.01
Pedagogical Content Knowledge		
Use strategies to teach CS concepts	0.85	0.01
Effectively monitor students' engagement in CS learning	0.84	0.01
Understand CS concepts well to be effective in teaching	0.88	0.01
Answer students' CS questions	0.76	0.01
Use equity practices to promote students' engagement in CS	0.76	0.01
Use inquiry-based teaching in CS	0.80	0.01
Use peer instruction strategies in CS classes	0.64	0.02
Help students understand CS concepts when they have difficulty	0.76	0.01
Get students interested in CS	0.85	0.01

Note: The survey items presented in this table are in abbreviated forms.

To establish convergent validity, we performed confirmatory factor analysis (CFA) using the PLS-SEM approach on the post-survey data. As shown in Table 2, the indicators have high loadings on the respective CK and PCK constructs and are significant ($p < 0.01$). Although 0.7 is a commonly used cut-off point for indicators' loadings on constructs, previous research has suggested that in social science, especially in new measurement development, it is common to have loadings lower than 0.7 [38]. As Hair Jr et al. [38] suggested, indicators with loadings between 0.4 and 0.7 should still be retained as long as they make an important conceptual contribution to the construct and if their removal does not significantly improve composite reliability. However, indicators with loadings lower than 0.4 should always be removed from the measurement model [3, 37]. Therefore, we used 0.4 as a cut-off value for factor loadings [38, 49]. Two items under the self-efficacy in CK construct had factor loadings below 0.4 and were thus removed (Impact2: I can identify the obstacles to equal access to computing among different demographic groups; and Impact4: I can

Table 3. Descriptive Statistics: Self-efficacy Survey

Constructs		N	M	SD
Content				
	Pre-survey	48	44.33	19.82
	Retrospective-before	51	43.25	22.58
	Retrospective-after (Post)	51	65.41	14.44
Pedagogical Content				
	Pre-survey	48	32.65	5.39
	Retrospective-before	51	24.59	10.54
	Retrospective-after (Post)	51	37.18	4.93

*Difference in sample size between the pre- and post-survey is due to missing data. Only matched pairs are included in the paired-sample t-tests.

identify the trade-offs between the beneficial and harmful effects of computing innovations on society).

In addition to factor loadings, we also examined the average variance extracted (AVE) to assess the level of variance in survey items captured by the CK and PCK constructs. The AVE score is 0.53 for CK and 0.63 for PCK, which meet the criteria for AVE to be above 0.5 [38].

In summary, both the factor loadings and AVE results suggest that the survey has a satisfactory level of convergent validity.

Discriminant validity. The heterotrait-monotrait ratio of correlations (HTMT) was used to check the discriminant validity in the CK and PCK constructs. The HTMT ratio between CK and PCK is 0.69, which conforms to the recommendation that the HTMT correlation values should be below the 0.9 threshold [40]. The HTMT results suggest that the survey has good discriminant validity between the self-efficacy in CK and PCK constructs.

Reliability. The reliability measures included Cronbach's alpha and composite reliability. The self-efficacy in CK construct reached Cronbach's alpha = 0.96, and the self-efficacy in PCK reached Cronbach's alpha = 0.91. The composite reliability for CK and PCK are 0.95 and 0.94, respectively, which exceeds the recommended threshold of 0.70 [38]. Both measures indicate that the survey has high level of internal consistency.

4.2 Measuring Changes in Self-efficacy

To answer the second research question, participants' responses to the pre- and post-self-efficacy surveys were compared. Table 3 shows the descriptive statistics of the survey results.

4.2.1 Self-efficacy in Content Knowledge (CK). The total score of the CK self-efficacy construct ranges between 18 and 90 for the 18 items, after removing two items based on the survey validation results described in the previous section. Using the pairwise deletion method, 47 matched pairs were included in the paired sample t-test for the pre-survey and post-survey, and 51 matched pairs were included in the paired sample t-test for the retrospective-before and post-survey. The paired sample t-test showed that the participants increased significantly from the pre-survey to the post-survey, $t(46) = 5.51$, $p < 0.001$, $d = 0.70$. Similarly, the participants' self-efficacy ratings on the post-survey were significantly higher than the retrospective before survey, $t(50) = 12.33$, $p < 0.0001$, $d = 1.79$.

4.2.2 Self-efficacy in Pedagogical Content Knowledge (PCK). The total score of the PCK construct ranges from 9 to 45 for the nine survey items. Using the pairwise deletion method, 48 matched pairs were included in the paired sample t-test for the pre-survey and post-survey. The results indicate significant increase from the pre-survey to the post-survey, $t(47) = 6.11$, $p < 0.001$, $d = 0.91$.

For the retrospective-before and post-survey, 51 matched pairs were included in the analysis. As described in the Data Analysis section, the change score from the retrospective-before to post-survey is not normally distributed. Thus, we used the non-parametric test, the Wilcoxon Signed Rank test, to compare the two surveys and found significant increase from the retrospective-before to post-survey ($z = 5.84$, $p < 0.001$).

5 DISCUSSION

5.1 Validation of the Self-efficacy Survey

Self-efficacy is an important construct in teacher education [71, 74], especially in a challenging discipline as CS [44]. This study contributes to the literature on teacher self-efficacy and CS education by developing measurement tools that focus on teachers' perceived capabilities in domain-specific tasks in CS teaching. Building on the recommended best practices in previous research [8], the self-efficacy items developed in this study are content-specific and may better predict future behaviors than items covering general dimensions [41, 48]. In addition, the survey validation results provide evidence that our self-efficacy survey has a satisfactory level of validity and reliability. The factor loadings of the survey items and the AVE statistics confirm that the survey has good convergent validity, suggesting that the items belonging to the CK and PCK self-efficacy constructs converge to reflect their respective construct. The discriminant validity statistics indicate that the CK and PCK self-efficacy constructs are empirically distinct. The high level of composite reliability and Cronbach's alpha also demonstrate that the survey has good internal consistency.

An implication of this study for the field of CS education is that it provides a validated measurement tool for examining CS teacher self-efficacy. Despite the important role of self-efficacy in teacher PD and effective CS teaching [48, 75], there have been limited tools available to assess this construct. In addition, previous research on teacher self-efficacy has mainly focused on instructional strategies in different content areas (i.e., PCK) [41, 75]. While such a focus is sufficient for experienced teachers in other fields, for CS teachers, it is also necessary to examine their self-efficacy in CK, given that most teachers in CS PD programs have limited prior exposure to CS knowledge [59]. Therefore, the survey developed in this study adds to the previous research by focusing on teachers' self-efficacy in the CK and PCK dimensions crucial to CS teacher development. Future studies should continue to explore the applicability of this measurement tool for other samples and CS PD programs.

5.2 The Influence of the PD on Teachers' Self-efficacy

Findings from this study showed that the participants of the TECS PD course significantly increased their self-efficacy in the CK and PCK for teaching CS, which is consistent with previous research that showed the benefits of PD programs for teacher self-efficacy [48, 65]. Aligning with the characteristics of the high-quality PD identified in previous research, the PD program in the current study encouraged active learning, collective participation, a strong focus on content, and was provided over a sufficient duration [22]. Thus, findings from this study corroborated previous research by showing that these high-quality PD components can also increase teachers' self-efficacy in CS. Considering that self-efficacy can influence teachers' persistence in the face of challenges and student outcomes [48, 71, 72, 82], results from this study demonstrate the benefits of structuring PD programs for CS teachers with high-quality PD components [22] to enhance teachers' self-efficacy in CS.

According to social cognitive theory, a potential rationale for the increase in teachers' self-efficacy is that the TECS PD provided teachers with mastery experiences [10, 48], or the successful experiences of accomplishing tasks, in the form of creating computing artifacts in the weekly online learning modules and practicing instructional strategies in micro-teaching sessions. Consistent with previous research that showed the association between teachers' satisfaction in past performance and their development in self-efficacy [74], the mastery experiences provided in the current study may have contributed to the significant gains in teachers' self-efficacy in the subject matter content and pedagogical content knowledge.

In addition, vicarious experiences may contribute to the significant increase in self-efficacy [7, 10]. For example, because the TECS PD course applied the Teacher-Learner-Observer model, the participants can obtain vicarious experiences through observing the teaching strategies appropriate for CS education as learners, observers, and teachers [32]. Moreover, the similarity between the social model and the self has been identified as a key factor in gaining self-efficacy through vicarious experiences [48]. In this study, the PD instructor became an effective ECS teacher through dedicated participation in ECS PD programs without a background in CS, which is similar to the participants' situations and could strengthen the influence of the social model on teachers' vicarious experiences to gain in self-efficacy. This follows what Bandura [7] refers to as "seeing people similar to oneself succeed by sustained effort raises observers' beliefs that they too possess the capabilities to master comparable activities required to succeed."

Similarly, social persuasion may have contributed to the teachers' gains in self-efficacy. In the PD course, the participants engaged in activities that afforded collective participation and social persuasion, such as providing peer review for each other on computing artifacts and receiving feedback from peers and instructors for their micro-teaching. Additionally, the social persuasions provided in the peer reviews and micro-teaching feedback focused on teachers' self-improvement and growth, which aligns with Bandura's recommendation on providing positive appraisals based on self-improvement rather than peer comparisons as a source for self-efficacy [5, 7, 9].

In summary, findings from this study suggest that CS teacher PD with high-quality components can enhance CS teachers' self-efficacy. In particular, CS teacher PD programs that provide mastery experiences, vicarious experiences, and social persuasion may facilitate the development of teachers' self-efficacy in CS.

5.3 Limitations

This study has limitations in sample size. As the PD program is one of the first CS teacher certificate programs in the state and requires high level of commitment, teacher participant recruitment and retention have been challenging, resulting in limited sample size. Data analysis methods that are more robust to limited samples were selected to address this issue. Another limitation is that the participants are high school teachers who chose to attend the PD program. As a result, the findings from this study may not be generalizable to other populations, such as teachers from other grade levels or those who are not interested in participating in such professional learning programs. Future studies are encouraged to validate the survey instrument to assess teachers' self-efficacy for different teacher populations and investigate potential variation in teacher self-efficacy development across grade and experience levels. Furthermore, this study did not assess instructional quality, student performance, or other more distal indicators as outlined in Desimone's conceptual framework for studying effects of PD and teacher belief [22]. Thus, we encourage future research to examine impacts of teachers' self-efficacy in CS on instructional practices and, ultimately, student performance.

6 CONCLUSION

This study is unique in the teacher education and CS education literature base, as it adds to the limited study on developing teacher self-efficacy through hybrid PD programs and bridges the gap in this research for in-service CS teachers. Teacher self-efficacy is often regarded as influential to teaching practices and student learning outcomes [59, 62]. The study reported in this article also responds to the call for research on teachers' engagement in hybrid teacher PD programs [14, 19, 20]. The primary contributions to the nascent teacher education literature base for CS teachers are two-fold: First, this study introduced, validated, and applied an instrument that measures CS teachers' self-efficacy. Second, this study indicated that participants significantly increased their self-efficacy in teaching CS from participating in the hybrid TECS PD course. These findings corroborate prior research in other STEM disciplines [74]. Consequently, teachers and other educational stakeholders should continue to explore the potential benefits of high-quality hybrid PD programs that, for example, provide teachers with active learning experiences.

In future research, it is necessary to explore whether changes in teacher self-efficacy relate to the quality of lesson designs and the teaching of the ECS course; and whether the teachers' subsequent teaching of the ESC course would lead to changes in self-efficacy.

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