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Coding attitudes of fourth-grade latinx students during distance learning

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ABSTRACT

Background and Context: Despite the growing initiatives in K-12 computer science (CS), there is a continued disparity in the participation of Latinx and multilingual students, a historically underrepresented group in computing. The inequitable participation may be understood by examining students' early development of CS attitudes.

Objective: This study aims to explore shifts and elicitation in coding attitudes of fourth-grade, Latinx students (ages 9-10) who underwent a year-long remote coding curriculum, with consideration of gender and language designation.

Method: Using a mixed method approach, pre-post survey responses on coding attitudes were analyzed to understand shifts and portrayal of Interest, Confidence, Utility, Social Values, and Perception of Coders, with consideration of gender or designation as an English Language Learner.

Findings: Gender and language designation did not interact with overall attitude shifts. However, there is a significant difference in Social Values and Confidence over time. Student interviews revealed more nuance in social influences with siblings and cousins as key motivators for extended learning, underlying values of perseverance in confidence, mixed perception of what coders do, and the importance of creativity to develop interest.

Implications: The key role of social influence in driving higher identity among Latinx students points to the important role of extended family. Moreso, developing students' confidence in domain-specific tasks should be a focus in curricula in order to have a longer-term impact on motivation. Finally, more research on the role that subjective task values pertaining to cultural values should be explored in early coding motivation in order to broaden participation. Keywords: Coding attitudes, elementary students, remote learning, expectancy-value theory, coding curriculum.

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Introduction

Computational thinking (CT) involves the ability to utilize knowledge of how computers work to solve problems (Wing, 2008). CT is not only vital for the field of computer science (CS), but also for interdisciplinary occupations that incorporate technology, such as media and arts (Pears et al., 2019). Computer-related occupations that integrate technology are

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predicted to be among the fastest-growing industries (US Bureau of Labor Statistics, 2020). Despite the vitality of CT abilities, participation and opportunity gaps in CS education persist among historically marginalized populations.

The Latinx population accounts for half of the population growth in the United States (US) and is the second-largest racial and ethnic group in the United States (Pew Research Center, 2020). Despite being among the largest demographic group in the nation, Latinx students compose only 10.4% of all students who obtained a bachelor's degree in CS, and Latinas compose 1.9% of the total CS degree (bachelor's, master's, and Ph.D.) recipients (National Science Foundation, 2018). This disparity is further exacerbated in the workforce, as 6.2% of employed computer scientists are Latinx and a low 1.2% are Latina (National Science Foundation, 2019).

Multilingual learners with English as a second language are among the fastest-growing populations in the primary and secondary school population. In the US, Latinx students constitute 77.6% of English Language Learners (ELL) in public schools (Institute of Education Sciences IES, National Center for Education Statistics NCES, and US Department of Education USDE, 2021). Similar to the disparities observed in higher education and the workforce, performance gaps exist in STEM education between students who are designated as ELL and those who are proficient in English (U.S. Department of Education, National Center for Education Statistics, and Common Core of Data, 2020). The prevailing perspective towards multilingual learners is that they are deficient in English proficiency, rather than recognizing them as individuals who are building language acquisition skills and valuable linguistic assets that can be effectively utilized (Lee & Stephens, 2020). Factors that hinder intersectional identities, such as being Latina or multilingual, from being fully integrated into the learning experience that is crucial for their academic progress, are considered to be responsible for the persistent disparity faced by Latinx and multilingual students.

CS education initiatives are formally expanding to include the elementary level due to the growing demand for the acquisition of computing skills and CT abilities (Code.org, CSTA, & ECEP Alliance, 2020). Despite the expansion of CS education opportunities in K-12, a participation gap persists among underrepresented groups. Latinx students comprise only 16% of Advanced Placement (AP) computer science exam takers (Code.org, CSTA, & ECEP Alliance, 2020). Additionally, Latinas compose 18% of all female AP exam takers despite making up 27% of the total female student population (Code.org, CSTA, & ECEP Alliance, 2020). This participation gap can have ripple effects on the participation of Latinx students in computing in higher education and the workforce, given experiences pertaining to a domain is a key variable for interest in pursuing the field (Sasson, 2021). A study in coding attitudes that begin in preadolescence can unveil the shifts and factors that contribute to this ongoing participation gap among underrepresented students.

This study investigates the attitudes of Latinx elementary students toward computer science, aiming to contribute to the literature on the development of motivation, attitudes, and perceptions in this field. Limited research exists on this development, particularly among young age groups, and even less so among underrepresented and marginalized groups (Kafai & Burke, 2015; Lambic et al., 2021). We analyzed surveys and interviews on coding attitudes through a mixed methods approach among fourth-grade students (ages 9–10) attending an urban school district with a predominantly Latinx, multilingual student population.

Students were exposed to a year-long CT curriculum through distance learning due to the COVID-19 pandemic. This study explores reveal significant changes in attitudes moderated by gender and designation as an English Language Learner (ELL) and how students elicit such attitudes.

Our findings highlight opportunities for future research in early coding motivation and the promotion of positive engagement among underrepresented youth, specifically focusing on the cultural group of Latinx. We will examine the significant impact of early exposure to a remote learning experience on the confidence and perceived social values of parents and peers. By conducting interviews with students, we explore how they expressed underlying social values that influenced their confidence and coding experiences as well as additional socializers to be considered for social values. Additionally, we discuss the limitations associated with early exposure in relation to the perception of coders and the utility, as well as the importance of creativity in fostering interest. Throughout the discussion, we identify potential areas for further research and expansion in the measurement and consideration of early coding attitudes.

Background

Attitudes toward CS among underrepresented groups often focus on secondary and higher education to address retention and remediation in academia and the workforce (Ni & Guzdial, 2012; Webb et al., 2012). The limited research on formations of identity and attitudes towards coding for preadolescent age groups has focused more on Science, Technology, Engineering, and Math (STEM; Capobianco et al., 2012). While research cannot pinpoint a critical period in time for such formation, several survey studies on STEM attitudes suggest that attitudes can be formed as early as elementary school (Carlone et al., 2014). Furthermore, problematic formations of STEM identity that are rooted in race, class, and gender can become apparent in sixth grade (Maltese, Melki, & Wiebke, 2014). Given these findings, this research is situated in a fourth-grade classroom, which is a crucial point in the development and evolution of student identity and attitudes toward CS.

We frame our approach and findings using the Situtative Expectancy-Value Theory (SEVT). SEVT takes a sociocognitive approach to studying attitudes under the lens of motivation. The theory posits that a student's motivation to pursue a career in a domain is dependent upon their expectancy to succeed and subjective task value for the tasks (Eccles et al., 1983). Obtaining high levels of both expectancy of success and task values increases the likelihood of a learner pursuing a domain. However, a student may obtain high expectancies of success (e.g. high confidence in a subject), but have low task values (e.g. perceived unusefulness of a subject).

The following sections will review prior works on attitudes with a focus on preadolescent age groups, Latinx populations, and the CS domain. First, this section will define attitudes through the lens of socio-cognitive theory. Next, prior works on early attitudes with a focus on the Expectancy-Value framework will be reviewed. Finally, literature on distance learning for elementary students will be considered to understand external factors that could inform the coding attitude outcomes in our study.

A sociocognitive perspective on attitudes

Sociocognitive theory pertains to "specif[ying] determinants of psychosocial change and the mechanism by which they produce their effects" (Bandura, 2005, pg 15). As such, attitudes are viewed as a cognitive mental state associated with an object that, in turn, influences behavior (Hogg & Vaughan, 2011). Attitudes are cognitive responses that help an individual navigate within an environment through a process of analyzing the self within a perceived world (Pratkanis & Greenwald, 1989). The creation of attitudes entails a process of labeling or attributing qualities towards an attitude object (or objects) that depend upon time and context (Pratkanis & Greenwald, 1989). These cognitive processes serve heuristic (labeling an object), schematic (organizational structure to guide memory and behavior towards an object), and self-related (association of object to self-worth) functions to ultimately relate the individual to a social world (Pratkanis & Greenwald, 1989). Attributions toward an object unveil a form of "knowing", such as coding as something that "boys just do" (Master et al., 2021).

Attitudes are argued to be an indicator of a forming identity (Hallajow, 2018), where identity involves a dynamic process of self-definition influenced by socio-contextual factors (Hogg et al., 1995). While preadolescents may not have developed a full identity, their environment already informs attitudes toward an object. Preadolescent age groups' perceptions, values, and attitudes toward education are highly influenced by their immediate social circles including teachers, friends, and parents (Eccles & Harold, 1996; Noack, 2004). These social influences mediate values and ideas through artifacts such as routines and norms, and preadolescents adopt such values to their objective realities and environment (Bronfenbrenner, 1979).

Problematic forms of STEM identity that are rooted in race and gender are apparent at the secondary education level, suggesting that attitudes and identity begin to form at an earlier point in development (Carlone et al., 2014; Master et al., 2016, 2021). This gender disparity in motivation has been linked to a decline in self-efficacy, interests, and values among students in higher education (Beyer, 2014). A sociocognitive lens allows for consideration of the influential role that social circles have on preadolescent age groups as we explore the perception and attitude towards CS.

Preadolescent attitudes of an academic domain

Attitudes towards task-oriented and formal learning environments have been explored from a cognitive perspective for preadolescent age groups. Prior works have identified attitude constructs for domain-focused contexts under the lens of motivation, which consists of factors such as self-efficacy, utility, or expectancy of success. Self-efficacy is an individual's belief that one can effectively perform as necessary in order to produce an outcome (Bandura, 1977). Utility alludes to a subjective task value that is connected to long-term goals and how useful a given task is in relation to those goals (Edwards, 1954). The expectancy of success refers to the probability that the individual believes they can perform a task, which is highly informed by self-efficacy (Atkinson, 1957).

The situated expectancy-value theory (SEVT) builds on the works of Bandura, Edwards, and Atkinson by expanding on the concept of expectancy of success and subjective task values to address the limitations of these constructs (Wigfield & Eccles, 1992). When it comes to choosing tasks, one can choose to perform a task to achieve a long-term goal despite their perceived ability. Furthermore, high self-efficacy does not translate to motivation to choose a task that they find little value in. Expectancy for success fails to inform motivation behind choosing tasks that are "risk-free", such as an ungraded assignment. As for utility, as it pertains to children, it overlooks the choice of completing a task that is irrelevant to an end goal.

Subjective Task Values capture individuals' tendencies to pursue tasks that are positively valued and help meets the needs of individuals (Eccles et al., 1983). This involves attainment values, incentive values, utility, and cost. According to Eccles, attainment value reflects ideologies or practices that individuals deem important and intrinsic value alludes to interest or enjoyment of a task. As such, individuals avoid tasks that are negatively valued due to contextual factors (Wigfield & Eccles, 2000). Cost is the consideration of limitations and efforts that can occur while pursuing a task (Wigfield & Eccles, 2000). Limitations can include tasks that contradict their values or prevents other tasks from occurring. Therefore, the SEVT framework considers motivation and attitudes from a socio-cognitive perspective.

The SEVT framework includes external factors or the cultural milieu that can influence expectancies of success and values. The cultural milieu involves socializers such as parents, teachers, and friend groups who translate beliefs, expectations, and attitudes (Wigfield & Eccles, 2000). As such, socializers influence a child's goals and self-schema such as their values, goals, self-abilities, and ideal self (Wigfield & Eccles, 2000). Such expectancies and values are ultimately informed by their sense of belonging and self-worth in a given space and time.

Coding attitudes among preadolescent

Early coding attitudes of preadolescent age groups have primarily revolved around the constructs of self-efficacy, utility, or expectancy of success to measure the impact of an intervention primarily in the form of a coding curriculum. Hermans and Aivaloglou (2017) and Kong et al. (2018) have explored whether certain coding activities have a significant impact on self-efficacy as defined by the perceived ability to perform a task and succeed in their tasks. Asad et al. (2016) studied whether certain design features, specifically interactive coding platforms, influenced self-efficacy through a lens of perseverance.

Other works have taken a more holistic approach to the impact of learning experiences on coding attitudes. Papavlasopoulou et al. (2018) used self-determination theory with a focus on competence, autonomy, and relatedness, which includes extrinsic motivations of the learning space. Mason and Rich (2020) used Eccles' Situative Expectancy-Value Theory to examine the impact of a coding curriculum intervention and developed the Elementary Student Coding Attitudes Survey (ESCAS), which will be used in this study.

The ESCAS measure identified five constructs to assess early coding attitudes among elementary-level students: Confidence, Interest, Utility, Perception of Coders, and Social Values. Figure 1 provides a visual representation of how we interpret the ways in which the ESCAS constructs relate to the SEVT framework, which is based on Wigfield and Eccles (2000). For the purpose of this study, the visual only includes elements of the SEVT model that directly align with the ESCAS measure.

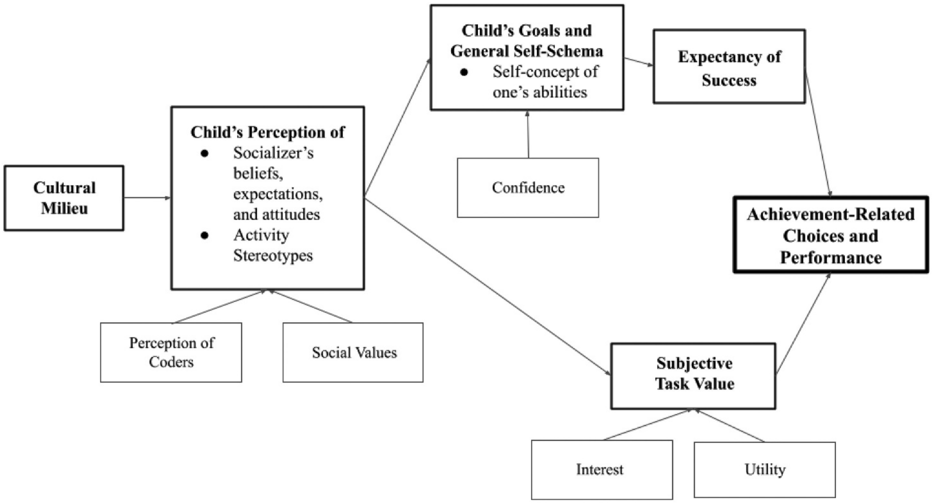

Figure 1. ESCAS constructs in relation to the SEVT framework.

Confidence, one of the constructs, reflects a student's perceived abilities and influences their Expectations of Success in coding tasks. This construct directly relates to the factor of Expectancy of Success. Next, Utility and Interest are constructs associated with Subjective Task Values. Interest refers to the positive feelings and values students hold towards coding as an activity (Mason & Rich, 2020). Utility, as mentioned earlier, represents the importance students place on tasks that align with their goals (Edwards, 1954). Additionally, the creators of ESCAS identified Social Values and Perception of Coders as constructs that are influenced by the cultural milieu. Social Values encompass students' perceptions of the goals, beliefs, and expectations of socializing agents, specifically teachers and parents. Perception of Coders, on the other hand, pertains to activity stereotypes or stereotypes related to the computer science profession, with the measure focused on the interdisciplinary aspects of coding.

The ESCAS tool did not identify factors that could be essential when considering coding attitudes of underrepresented students, specifically cost and perceptions on stereotypes related to gender and race/ethnicity. The creators initially took into account gendered stereotypes in their analysis, but these specific items were found to have limited significance for their sample, which predominantly consisted of white students.

Existing, published work has yet to explore the early coding attitudes of the demographic subgroups of Latinx, Latinas, and multilingual students. CS as a field is a socially constructed entity informed by years of a biased culture shaped by affluent white males. The perception of attitudes pertaining to who "can and cannot" do coding is a product of deficit belief systems that remain from the racial and sexist history of the past (Margolis et al., 2017). To effectively address the root cause of these participation gaps among historically marginalized groups, CS must be viewed as an artifact that embodies a culture that influences these attitude formations. Therefore, we must consider the extent to which measures associated with CS include or exclude factors that influence to diverse, underrepresented groups.

Primary computer science education (CSE) studies focusing on Latinx groups have contributed to inclusive participation practices by considering literacy and multilingualism (Jacob et al., 2020; Vogels, 2021). These studies in CS literacy aim to incorporate the language assets of multilingual students, fostering their participation in CS activities (Jacob et al., 2020; Vogels, 2021). This approach involves addressing harmful dominant practices in literacy (Vogels, 2021). Additionally, students' computational practices they engage in is driven by the motivation to share their background, such as interests and enjoyment (Jacob et al., 2020).

Distance learning for students of low-SES households

This study was conducted in a distance learning approach to learning due to the COVID-19 pandemic. We consider the impact that remote instruction has on the formation of coding attitudes, especially in communities of low socioeconomic status (SES). Learning in a remote environment heavily relies on a student's ability to work independently which involves time management, active listening, and concentration (Sherry, 1995). For educators, establishing a relationship with their students becomes challenging, as they must explicitly establish both an authoritative and mentorship role for students to maintain academic performance and high participation (Sherry, 1995; Burdina et al., 2019). This places parents in a vital role in a children's learning process. However, parents from low SES households are more likely to face obstacles in providing a digital environment and support in their child's learning experiences due to limited access to quality technology or limited knowledge (Aguilar et al., 2020; Vogels, 2021).

Methods

In this study, we utilized a concurrent triangulation mixed-methods approach to examine the coding attitudes of fourth-grade students in a year-long remote coding curriculum. We collected and analyzed both quantitative and qualitative data simultaneously (Rauscher & Greenfield, 2009). Quantitative analysis of a survey explored changes in attitude constructs, focusing on gender and English Language fluency. This statistical phase provided insights and identified significant patterns. At the same time, qualitative analysis of student interviews complemented the quantitative findings, offering a deeper understanding. Triangulating the results allowed for a comprehensive exploration of coding attitudes, with a specific focus on how Latinx students expressed these constructs. Our concurrent triangulation integrated parallel data collection and analysis, enhancing the robustness and comprehensiveness of the study's findings.

The mixed-method approach was employed to triangulate multiple datasets and complement the findings by addressing the same research questions. The research questions that guided this study were: *How do students' expectancy values toward coding change over the course of a year-long, remote coding curriculum? Are these changes moderated by gender and designation as an English Language Learner, separately? How do children elicit their expectancy value towards coding?*

Coding curriculum

The curriculum for this study is an adaptation of the prior curriculum on block-based coding like the Scratch platform and was modified to cater to the Latinx, multilingual learners of our partner district (Saito-Stehberger et al., 2021; Zhang & Nouri, 2019). The curriculum was designed to integrate English Language Arts and included effective strategies for ELLs in STEM subjects (National Academies of Sciences, Engineering, and Medicine, 2018). These strategies aim to support the development of academic language in a content area by embracing students' home language and cultural assets while also providing diverse ways to support language comprehension of the discipline. For example, every unit begins with prompts that ignite student background knowledge of a concept before introducing the term (e.g. "What actions do you do in order to cause something else to happen?" for Events). The curriculum also includes a "Memorable Role Models" activity that highlights female and computer scientists of color for our students to relate to.

The coding instruction and assessments were initially designed for in-person instruction. In preparation for distance learning due to the COVID-19 pandemic in the 2020–2021 school year, aspects of the curriculum were modified to support distance learning. Such modifications included videos for asynchronous instruction, converting student workbooks into Google forms to turn in assignments, and lecture slides that would support remote synchronous teaching. Remote teaching strategies varied as some educators taught the lesson synchronously or provided coding activities as an asynchronous assignment.

Participants

This study was conducted during the third year of a partnership between university researchers and a local public school district. The school district has a student population that is predominately Latinx (96.1%) and of low socioeconomic background (87.0%) (Educational Data Partnership, 2019). Prior to this partnership, the district did not implement a formal curriculum or training for primary educators to teach CS.

District members and principals nominated educators across six schools to participate in the research project and offered monetary compensation for participation. A total of 12 educators volunteered to participate, which involved data collection tasks, attendance to professional development sessions throughout the school year, and teaching a CT curriculum to their students for one hour a week. The research team selected five educators for case study analysis and were chosen based on their years of experience with the curriculum (e.g. novice, experienced) and the type of school they attended (e.g. dual immersion programs where home languages and English are used in teaching).

Educators were tasked to distribute assessments developed by researchers, which included a pre and post survey on coding attitudes (Mason & Rich, 2020) and CT knowledge (Parker et al., 2021). The assessments were delivered as online forms and delivered remotely. Educators distributed the pre-test before coding instruction began and the post-test the last month of the school year in May. Some educators had students complete these surveys as asynchronous assignments and other educators conducted the surveys synchronously to ensure completion. The total number of responses received for the pre-test on coding attitudes was 263 participants and the post-test was 219. Two teacher participants did not conduct the post-test in time before the end of the school year due to complications in scheduling. This analysis only included students that completed both pre and post tests. The final sample size is 181, composed of 102 female students and 62 students designated as English Language Learners (ELL). The district provides initial language proficiency testing for incoming students to the district to determine designation as an ELL learner.

Student interviews were conducted virtually throughout the school year for the purpose of gathering insight into students' developing coding identities. The case study educators were tasked to select six case study students to be interviewed using criteria developed by the research team, which aimed for a selection of a range of students based on their proficiency in the English language, perceived coding abilities, and equal representation of gender. These interviews were conducted one-on-one through a video platform during school instruction. Student interviews were scheduled upon completion of the second unit, out of a total of five units, to capture attitudes upon initial exposure to the Scratch platform. Due to scheduling and the varied pace of each educator, student interviews were conducted between November and May. Furthermore, not all selected case study students were able to be interviewed and included in the analysis. A total of 13 student interviews were gathered which included seven female students and six male students. Seven of these students were designated as ELL and two of the students were redesignated to be English Proficient.

Researchers and positionality statements

Given the importance of studying the computer science attitudes of Latinx students, a historically marginalized group in the field, it is crucial to acknowledge the positionality of the authors. The first author, a bilingual Latina, brings both practitioner and research experience in STEM learning among underrepresented communities. Her analysis is shaped by her personal background growing up in a Mexican-immigrant household and community, which is reflective of participants in the study. Additionally, as a first-generation college student who pursued a STEM degree, her perspective offers insights into the factors that influence motivations to pursue such careers. The second author, a monolingual White woman, has extensive expertise in computer science and computer science education, with a focus on equity and inclusion in K-12 pathways. Her experience pursuing a degree in a male-dominated field is also a perspective that enriches the study. Finally, the last author is a multilingual White man with a background as a former Spanish-bilingual math and language teacher in various countries. This experience provides valuable perspectives on educational equity for diverse learners, highlighting the role of culture in shaping academic motivation among Latinx students.

Measures and analysis

Elementary student coding attitudes survey

The Elementary Student Coding Attitudes Survey (ESCAS) is a validated measurement for preadolescent age groups, specifically fourth to sixth grade (Mason & Rich, 2020). The authors identified five latent constructs for early coding attitudes: confidence (C), interest (I), utility (U), perception of coders (P), and Social Values (S). The survey consists of a total of 23 items that measure across the 5 constructs, using a 6-point Likert scale with *strongly agree, agree, somewhat agree, somewhat disagree, disagree*, and *strongly disagree*. The ESCAS survey does not provide a neutral option and thus uses a forced-response approach. The ESCAS survey use of a six-point Likert scale can be justified as a continuous scale and can be treated as interval data (Norman, 2010).

A two-way repeated measures ANOVA was performed to determine whether there is an interaction between the *designation as an ELL student* (ELL and Non-ELL) and *time* (Time 1 and Time 2) on coding attitude scores (CAS) as well as *gender* (Male and Female) and *time*. Time 1 refers to the pretest and before exposure to the coding curriculum, and Time 2 refers to the posttest and after exposure to the coding curriculum. First, the correlation coefficient was calculated to assess the linearity between items and normality of the dataset (see Appendix A). Next, the Shapiro-Wilk test and QQ plots were used to confirm the normality of our dataset (see Appendix B). A repeated measures ANOVA was also used to provide insight into within groups (e.g. ELL and Gender) interrelations.

The R function anova_test that was used for ANOVA analysis provided eta-squared ($\eta 2$) as the determinant for effect size (Kassambara, 2021). Eta-squared is the proportion of the total variability of the dependent variable as accounted for by the variation in the independent variable (Fay & Boyd, 2012). We follow the general rule for eta-squared effect sizes; $\eta 2 = 0.01$ indicates a small effect, $\eta 2 = 0.06$ indicates a medium effect, and $\eta 2 = 0.14$ indicates a large effect (Cohen, 1988).

For post hoc analyses, we use the Bonferroni correction for four comparisons. In this study, we conduct two separate two-way ANOVA for each factor (i.e. gender and language designation) to examine the interaction effect on a computational thinking assessment across two-time points. This results in a total of 8 pairwise comparisons, with each factor consisting of four pairwise comparisons (i.e. two conditions with two-time points). A significance level of .05 will be adjusted to 0.00625 to account for the error rate.

A Confirmatory Factor Analysis (CFA) was used to calculate weighted scores from standardized factor loadings. CFA provides factor loadings of theory-driven relationships across constructs (Bollen, 1989). The weight of each item was determined by standardized factor loads and rescaled to one to six to allude to the use of a six-point Likert scale.

Coding attitudes student interview

The interview protocol was designed to explore the constructs identified in the ESCAS survey, as seen in Appendix I. The protocol did not include all factors of the SEVT model, such as cost. The interviews had a duration of fifteen minutes to simplify scheduling and minimize time away from school instruction. Student interviews were audio recorded and

Table 1. Coding attitude codes and definitions.

Code	Definition	Example
Interest	Expressing deep knowledge of, positive feelings toward, and value for activities, practices, or professions associated with coding or the activities in the curriculum.	*"I also think about things that I should challenge myself to do. Like for example, probably even a big game like Minecraft"*
Confidence	Expressed belief in, or recalled experience of, self abilities to complete a particular task or fulfill a particular role within specific skills and aptitudes shown to be useful in coding.	*"I think yesterday we were coding in Scratch. So I went to go back to the [student workbook] and I figured it out".*
Utility	Perceived usefulness of coding in terms of how a coding task or practice fits into an individual's current or future plans, outside of the expected task.	*"Well, computer science has programs. If I need some programs to help with eyesight, ear hearing and stuff like that, helpful for people around the world."*
Perception of Coders	Existing stereotypes or preconceived ideas regarding what it means to be or do coding, coders, and/or the coding profession.	*"A computer scientist is someone it's like a scientist, but they work on computers a lot."*
Social Values	Mention of social circles or influences as experiences, sentiments, or behaviors towards coding are described.	*"I enjoy doing programming with my programming teacher is what gave me the support".*

transcribed using software and human transcribers. A lead researcher and two undergraduate research assistants developed a codebook through an iterative deductive process. The qualitative research codebook underwent a rigorous process to establish reliability and agreement. Initially, four interview transcripts were independently coded by each researcher. Collaborative discussions were held among the researchers to reconcile any discrepancies and achieve consensus on excerpts that shed light on coding attitudes. This iterative process not only refined the definition of each code but also ensured consistency across interpretations. The refined definitions of the codes can be found in Table 1. To further enhance reliability, the remaining interviews were divided among the researchers and independently coded. The qualitative analysis was not designed to determine qualitative differences between gender and ELL students. Instead, it is composed of equal representation of each student group to reach saturation in the ways in which the attitude constructs are elicited (Saunders et al., 2018).

Findings

Coding attitudes survey

A weighted factor score was calculated using CFA to determine how much a survey item informed an attitude construct. The post-test was used for CFA analysis since the summation of Likert responses met normal distribution and had a stronger correlation than the pre-test scores. The Comparative Fit Index (CFI) resulted in 0.887 and the Tucker-Lewis Index (TLI) was 0.870, which is close to the acceptable range of good fit of 0.95 or above (Dion, 2008). The Root Mean Square Error of Approximation (RMSEA) was 0.066 and the Standardized RMSEA was 0.070, which is an appropriate limit (Dion, 2008). These findings indicate that the model provides a reasonably accurate representation of the data and therefore appropriate to use the factor scores of the model.

Table 2. ESCAS survey items, standardized weighted, and mean differences between time.

EVT Construct	Item	Std Weight	Pre	Post	Mean Diff
Confidence	C1: I can learn to code.	0.75	3.38	3.56	0.185
(HPS = 22.2)	C2: I am good at coding.	0.81	2.73	3.14	0.405
	C3: I am good at problem solving.	0.48	2.05	2.12	0.067
	C4: I can write clear instructions for a robot or computer to follow.	0.57	1.95	2.14	0.185
	C5: If my code doesn't work, I can find my mistake and fix it.	0.59	2.58	2.77	0.196
	C6: I've been told I would be good at coding.	0.50	1.58	1.82	0.233
Interest	I1: I like coding, or I think I would like coding.	0.82	3.42	3.71	0.299
(HPS = 23.4)	I2: I would like to learn more about coding.	0.85	4.18	3.96	-
	I3: Solving coding problems seems fun.	0.78	3.43	3.41	0.217
	I4: Coding is interesting.	0.76	3.53	3.77	−0.026
	I5: I would like to study coding in the future.	0.68	2.96	2.78	0.236
Utility	U1: I can use coding skills in other school subjects.	0.68	2.76	2.95	−0.173
(HPS = 15.2)	U2: Knowing how to code will help me to create useful things.	0.68	3.05	3.15	0.188
	U3: Knowing how to code will help me solve problems.	0.66	2.85	2.87	0.105
	U4: I think I will need to understand coding for my future job.	0.52	2.05	1.94	0.022
Social Values	S1: My friends think coding is cool.	0.53	2.05	2.28	−0.114
(HPS = 9.61)	S2: My parents think coding is important.	0.33	1.29	1.37	0.235
	S3: I am friends with kids who code.	0.75	2.32	3.14	0.079
Perception	P1: Kids who code are smarter than average.	0.60	2.35	2.44	0.820
(HPS = 19.0)	P2: Kids who code enjoy doing sports.	0.54	1.83	1.82	0.090
	P3: Coders are good at math.	0.69	3.03	3.12	0.006
	P4: Coders are good at science.	0.67	2.95	3.08	0.091
	P5: Coders are good at language arts.	0.65	2.56	2.64	0.130

HPS = Highest Possible Score.

Table 3. Weighted sum mean scores in time 1 and time 2 and by groups.

		Pre	Post	
	N	M SD	M SD	M Diff
Total	181	6.9 9.94	64.0 1.8	3.1
ELL	62	59.4 1.8	62.8 9.43	3.4
Non-ELL	119	61.7 9.39	64.7 11.5	3.0
Female	102	6.6 9.75	63.2 11.1	2.6
Male	79	61.2 1.2	65.0 1.5	3.8

Table 2 provides the resulting standardized factor loads for each survey item which were all above the 0.32 cutoff (Worthington & Whittaker, 2006). The descriptive statistics of the weighted scores across time and by groups can be found in Table 3 below. The box plots that visualize the pre and post differences across the SEVT indicators and by groups can be seen in Appendix C to Appendix H.

Assumptions for ANOVA were tested to ensure the weighted data scores are appropriate for analysis in terms of normality and identifying outliers. The Shapiro-Wilk test was conducted on the total weighted mean scores in Time 1 and Time 2. According to the test, the coding attitude score was normally distributed in Time 1 ($p = 0.562$; $p > 0.05$) but not in Time 2 ($p < .001$). After consulting the QQ plots, which can be seen in Appendix B, we confirmed that most data points fell along the reference line with a few outliers at the left. Therefore, we assume normality for our data.

Eight extreme outliers were identified and were representative of students that are important for our study, with five students designated as ELL and seven students who are female. The two-way ANOVA test was conducted with and without these outliers and

Table 4. Mean Scores and differences of SEVT constructs in time 1 and time 2 and by group.

	T1		T2				T1		T2		
	M	SD	M	SD	M Diff		M	SD	M	SD	M Diff
Interest (HPS= 22.2)						Social (HPS= 9.61)					
Time	17.5	3.96	17.6	4.56	0.12	Time	5.66	1.77	6.80	1.76	1.14
ELL	16.4	3.42	17.3	4.38	0.90	ELL	5.61	1.86	6.51	1.77	0.90
Non-ELL	18.1	4.10	17.8	4.66	-0.30	Non-ELL	5.69	1.72	6.95	1.74	1.26
Female	17.4	3.67	17.4	4.68	0.00	Female	5.78	1.61	6.68	1.78	0.90
Male	17.7	4.32	18.0	4.41	0.30	Male	5.51	1.95	6.94	1.73	1.43
Confidence (HPS = 23.4)						Perception (HPS = 19.0)					
Time	14.3	3.07	15.5	3.33	1.27	Time	12.7	2.77	13.1	2.78	0.40
ELL	13.8	3.31	15.1	3.22	1.30	ELL	13.0	3.32	13.0	2.86	0.00
Non-ELL	14.5	2.92	15.8	3.37	1.30	Non-ELL	12.6	2.43	13.1	2.74	0.50
Female	14.0	2.85	15.1	3.46	1.10	Female	12.7	2.60	13.1	2.52	0.40
Male	14.7	3.30	16.1	3.08	1.40	Male	12.7	2.99	13.1	3.09	0.40
Utility (HPS = 15.2)											
Time	10.7	2.19	10.9	2.27	0.20						
ELL	10.5	2.19	10.8	2.12	0.30						
Non-ELL	10.8	2.19	11.0	2.35	0.20						
Female	10.7	2.22	10.9	2.29	0.20						
Male	10.7	2.15	10.9	2.26	0.20						

HPS=HighestPossibleScore,T1=Time1orPretest,T2=Time2orPosttest,M=Mean,SD=StandardDeviation, MD=meandifference.

Table 5. Results of repeated measures two-way ANOVA by SEVT construct. * p < 0.00625.

	F	p	η2		F	p	η2
Total				Utility (U)			
ELL Status	3.34	0.068	0.009	ELL Status	1.09	0.297	0.003
Gender	1.23	0.269	0.003	Gender	0.05	0.826	0.00†
Time	8.15	0.005*	0.022	Time	0.73	0.395	0.002
ELL X Time	0.03	0.858	0.00†	ELL X Time	0.02	0.896	0.00†
Gender X Time	0.30	0.584	0.00†	Gender X Time	<0.001	0.978	0.00†
Interest (I)				Social (S)			
ELL Status	5.57	0.019	0.015	ELL Status	1.78	0.184	0.005
Gender	0.90	0.344	0.003	Gender	<0.001	0.980	0.00†
Time	0.07	0.788	0.00†	Time	0.63	<0.001*	0.095
ELL X Time	1.87	0.172	0.005	ELL X Time	0.86	0.353	0.002
Gender X Time	0.13	0.716	0.00†	Gender X Time	2.09	0.150	0.006
Confidence (C)				Perception (P)			
ELL Status	3.53	0.061	0.010	ELL Status	0.39	0.536	<0.001
Gender	6.51	0.011	0.018	Gender	<0.001	0.970	0.00†
Time	14.3	<0.001*	0.039	Time	1.81	0.180	<0.001
ELL X Time	<0.001	0.998	0.00†	ELL X Time	0.87	0.351	<0.001
Gender X Time	0.16	0.692	0.00†	Gender X Time	0.02	0.886	0.00†

*p<.006,
† is < 0.0001

resulted in similar outcomes when analyzing the difference in ESCAS scores across time, gender, and designation of ELL. Both analyses resulted with time as the only significant difference. Without outliers, time (F = 13.4, *p* < .000) was significant with a small effect size of 0.038. In comparison to time (F = 8.18, *p* = .004) with outliers with a smaller effect size of 0.022, as seen in Table 4 below. Given that the aim of this study aims to understand the coding attitudes of underrepresented students in CS, the identified outliers were kept in our analysis.

The ANOVA analysis showed that while there are significant changes to coding attitudes across time, there were no meaningful differences in coding attitude scores based on gender or English Language Learner status. As displayed in Table 5 below, there are no statistically significant two-way interactions between gender and time ($F = .30$, $p = .269$) or between the designation of ELL and time ($F = .03$, $p = .068$) on coding attitude scores. Such is the case within SEVT constructs, as well. The overall ESCAS had a significant difference before and after exposure to the remote coding curriculum with a small effect size ($F = 8.15$, $p = .005$, $\eta 2 = 0.02$).

Additionally, the results show that there are significant changes across time when we look at each attitude construct separately. Within each SEVT construct, confidence and social values had a significant difference before and after exposure to the remote coding curriculum with confidence having a small effect size ($F = 14.3$, $p < .001$, $\eta 2 = 0.04$) and social values having a moderate effect size ($F = .63$, $p < .001$, $\eta 2 = 0.10$).

Student interviews

To obtain insight into confidence, we looked at comments on the ability to "learn to code" and instances when children reflected on programming instances such as debugging. Students generally expressed the capability to grow in their coding abilities and to learn to code. This was further elicited when students described feelings towards the process of "fixing" their code, such as confidence or capabilities in resolving problems in their program. However, many students acknowledged that fixing their code would require some perseverance if there was an issue. As a student, Laura (all names are pseudonyms), reflected on having mistakes in their program, she said, "I feel kind of upset, but I still think that I can make it happen". In a similar manner, students acknowledged that fixing problems can help their learning process, which can allude to the motivation behind persevering mistakes in their program. As a student, Karina, mentioned, "I feel a little sad, but then again, I feel happy. Cause then I know that doesn't work. So I know that I can try something else. I learned from my mistakes. So I know I can try something else and remember that, that doesn't work".

In relation to interest, students expressed positive sentiments toward their learning experience and willingness to learn more. Interest in coding was strongly connected to the storytelling and personalization nature of the Scratch platform that allows for "creat[ing] our own creations", as a student Hector shared. This agency for creativity enhances their interest and motivation to teach themselves new features and blocks on the platform. For example, one student, Mandy, recalled, "My favorite project that I made is the About Me project because I got to use my creativity in most of the projects. And I did a little bit more learning and hard work on it and I did art that took me some hours". The "little bit more learning" in her case consisted of learning code blocks outside the curriculum, such as the broadcast feature.

Students expressed an agreement to the "importance" of coding and the CS profession, but for a range of reasons. Most students reported how CS was helpful in enhancing technology for social impact or benefitting society. Among them was Karina, who immediately associated computer scientists with futuristic designs: "Um, they could code, they could code like the plans for the first flying car or the first digital phone. I'm just thinking of stuff as digital in the future". Some students associate the importance of the profession with the advancement of technology for society, like when Hector acknowledged how technology is used everywhere through machinery: "Some people use computers.

Sometimes they create stuff they could use. And so they learn how to use it and they start using it a lot better".

Students' perceptions of coders went hand in hand with their description of the importance of CS. For the most part, they associate coders as creators, innovators, and problem solvers of technology. Some students even mentioned their teacher as an example of a computer scientist. However, not all students were able to respond and provide a description of a computer scientist beyond that of what they have experienced in the classroom. For example, Josh defined a computer scientist as "[T]hey could learn more in computer science and coding classes". But when prompted on how that can "make the world better", he shrugged and could not elaborate further.

To understand the social influences of our students, the interview questions prompted students to disclose any discussion of or experiences in coding outside of the classroom. Three students reveal having a relative who is a computer scientist, while the majority do not have access to individuals that work in the computing field. Still, the majority of students mentioned that they have shown or discussed their coding projects with their family and friends. While not all students mentioned parents, many disclosed coding with their cousins or siblings. As Hector mentioned "Well, I talk about it sometimes . . . [I] talk about it with my little brother and we do stuff, fun stuff, our own creations". Siblings continue to be an influence for most students, like Carol who said "My parents think [Scratch] is like homework because, um, they don't really know because they speak Spanish. Well, my brother will understand if I explained it to him".

Given the storytelling nature of Scratch, their social circles are sources of inspiration for their project topics. As Karina mentioned, "[I]t's for my siblings that I've been wanting to make for almost for forever . . . cause my siblings are obsessed . . . they will always want to use my phone . . . I want to make an animation about, um, phone addiction". Her willingness to teach her siblings about technology habits is a clear motivator for Karina to plan for projects beyond the curriculum. At the same time, sharing with others is a motivation for students to pursue their passion projects, with students like Melanie who expressed eagerness to share her project virtually: "I'm going . . . continue working on this one so I can just show my class so once I'm done so I'm gonna collect my friends and then I'm gonna show my friends on like I think a zoom. . ."

Discussion

Previous research has established the association between attitudes and behavior, underscoring the role of behavior as an indicator of developing identity (Hallajow, 2018; Hogg & Vaughan, 2011). Our study examines the attitudes of young students towards computer science education after exposure to a year-long remote curriculum, utilizing survey and interview data. The significant difference between the pre and post-test scores across time can be informed by the mean difference of social values (*MD*= 1.14) and confidence (*MD*=1.27). Attitudes serve as a cognitive process that relates individuals to their perceived world (Pratkanis & Greenwald, 1989), and our findings show that social values and confidence are key factors when considering early formations of coding attitudes among Latinx students. Through our analysis, we highlight findings that contribute to the existing literature and emphasize the significance of this work.

Social values

The significant change in perceived social values of parents and teachers echoes the importance that socializers have on children (Eccles & Harold, 1996,; Noack, 2004). As we look at the items that inform social influence, displayed in Table 2 above, we see the most gain was in item S3 *"I am friends with kids who code"* (*MD*=.820) and item S2 "*My friends think coding is cool*", (*MD*=.235). Exposure to coding with a classroom of peers can inform the perception of having "friends" who code, while item S2 gives insight into the perceived positive views that peers have towards coding. This confirms prior work which indicated that preadolescent students' attitudes are influenced by their immediate social circles (Eccles & Harold, 1996; Noack, 2004). Moreso, our findings show that virtual learning environments with familiar peers can also influence coding attitudes.

Literature has shown that preadolescent age groups are primarily influenced by their parents more so than their peers (Wigfield et al., 2015). Students indicate that coding discussions at home with parents revolve around the projects they have created as part of the course or emphasize the importance of learning to code, which can inform the small change in item S3 "*My parents think coding is important*" (*MD*=.079). Yet, interview findings indicated that parents are not the sole socialization influences for at-home learning, as students reported engaging in coding discussions and practices with siblings and cousins.

While studies on socializers have primarily focused on teachers and parents as influential figures, there has been less exploration of other familial relationships (Simpkins et al., 2020). The involvement of extended social circles may arise from parents' limited awareness of technology, the US education system, or demanding work schedules (Aschbacher et al., 2010). In the context of computer science, students often seek guidance from individuals in their immediate circles who actively use technology in their daily lives or have knowledge of coding platforms, such as older siblings experienced with Scratch. This finding reveals the need for studies on motivation in technology-oriented fields to consider social values beyond the parent-child dynamic. Consequently, evaluative tools assessing early coding motivation should incorporate items that reflect how social circles and their relationship to technology can impact motivational factors.

The qualitative findings of this study provide valuable insights into the influence of social circles on the content of coding projects. Students emphasized that their coding projects were often driven by a desire to assist and benefit their families. These findings shed light on the underlying motivations and subjective values that shape students' engagement with coding. It is evident from our research that the value of aiding their families is deeply ingrained in students' coding practices. This value aligns with the concept of attainment value, which reflects the significance students attribute to certain activities and informs their personal values and aspirations (Eccles et al., 1983). Our findings reveal the need to enhance the ESCAS measure by considering not only interest and utility but also the role of other values, particularly those influenced by students' cultural backgrounds, in the early stages of coding motivation development.

Confidence

As seen in Table 2, we see the confidence item with the greatest increase was C2 "*I am good at coding*" (*MD*=.405), which represents an increased expectancy for success in this domain. Our analysis of the student interviews further shows that students have a perceived ability and capability of growth of general coding skills, which involves fixing their programs for their storytelling project. Yet, we do not see a lower increase with items that allude to the attainment of fundamental CT skills with C4 "*I can write clear instructions for a robot or computer to follow*" (*MD*=.185), which represents the understanding of the concept of algorithms, and C5 "*If my code doesn't work, I can find my mistake and fix it*" (*MD*= .196), which is representative of the practice of debugging. Similarly, the smallest increase among all confidence items was C3 "*I am good at problem solving*" (*MD*=.067). Maintenance of confidence and self-efficacy in coding is rooted in the belief to succeed in tasks or roles that are deemed as essential for a domain, such as algorithms, debugging, and problem solving.

Ensuring that students feel confident in specific coding skills is essential to maintain their overall confidence and belief in long-term success. When comparing cultural groups, it is evident that underrepresented students, particularly those with intersecting identities such as gender and race, tend to express less confidence in coding compared to their more privileged peers (Salguero et al., 2021; Román-González et al., 2018; Kallia & Sentence, 2018). Moreover, it emphasizes the need for explicit strategies to build coding-specific skills and confidence (Garcia et al., 2023), utilizing existing processes to foster this confidence.

This finding also questions what students associate coding with and whether there is a clear connection between coding on the Scratch platform and the general skills required to work with robots or computers. Prior studies on children's understanding of computer scientists and computers revealed that children described actions such as "typing" and "making" as actions that computer scientists do, while simultaneously using vocabulary such as programming and coding (Hansen et al., 2016). Student interviews did not dive deep into terminology they associate with CS, but our findings from the qualitative interview show that students' perceptions of what computer scientists do revolve around the improvement of various forms of technology. However, not all students were able to make this connection to the greater impact of CS and limited their definition to the acts of coding. This indicates that students' perceptions of coding at the elementary level have mixed results and further research is required to determine such differences.

It is apparent that children have challenges with transferring ideas from the immediate and tangible experience that is a block-based Scratch program, to coding objects they are aware of in their world such as robots or computers that they have yet to explore. However, we acknowledge the difficulty in the transfer can be due to remote instruction, as there is a greater disconnect between educators and students to ensure academic performance (Burdina et al., 2019). Additionally, a year-long curriculum is not enough to make such connections for this age group. Policymakers and curriculum developers should address this gap in knowledge transfer and awareness regarding the diverse impact and practices encompassed in computer science within learning trajectories.

Qualitative findings highlight the connection between students' perseverance and their confidence in their learning abilities. Students emphasize the value of practice and learning from mistakes when describing their capability to learn Scratch. This is reflective of the cultural Latinx value of *ganas*, or the will to succeed that is often practiced when it comes to education (Azpeitia & Bacio, 2022). Overall, the mixed findings reveal that deeper social values that are reflective of their cultural background can be informing coding confidence. Future work is needed to expand on social and cultural forces that influence elementary grade students.

Perceptions, utility, and interest

There were no significant changes in Utility and Perceptions across time or between our groups of interest. The coding intervention had minimal impact on students' view of coders as being interdisciplinary across subjects (perception) and as something that is useful for their current or future goals (utility). The interviews showed that students indeed view coding and CS as important for the general world, with descriptions of how technology can better help individuals or even how storytelling through Scratch can bring awareness to topics. Yet, there was no qualitative evidence as to a connection between coding and their immediate lives, much less on the interdisciplinary view of coding (e.g. Coders are good at language arts).

General outcomes regarding the utility obtainment during early coding exposure at the elementary level have been inconsistent. Research has shown that students find coding to be useful when exposed to a variety of coding platforms, including both block-based coding and syntax-based languages such as Python and Racket (Liu et al., 2022). However, the use of only visual programming platforms like Ozobot and Dash and Dot did not yield the same level of utility (Sáez López et al., 2021). These results suggest that the utility of coding may depend on the specific coding experiences informed by the platform and the challenges encountered.

The lack of significant change of utility could be attributed to the limited exposure students have to practice coding. Specifically, a year of exposure and the use of only the Scratch platform may not be enough for students to significantly grow in how they view coding as relevant to their personal goals. Additionally, along with the limited perception of coders and impact of coding, our results indicate that students early coding motivation is perhaps irrelevant to personal end goals (Wigfield & Eccles, 2000). However, that is not to say that interventions cannot begin to instill utility and better perception of coders for this age group.

Early exposure to coding has been found to increase future interest in the field (Miller, 2018). Despite the lack of significant changes in interest, the qualitative evidence showed that developing interest was tied to the creative freedom that the students engaged in. This aligns with a similar study wherein interest in learning the content was due to creative practices of the activity which include self-creation, experimentation, and independent learning (Liu et al., 2022). The remote coding curriculum took on a structured inquiry approach, where students are given projects to create but have a sense of creative freedom to personalize their projects on the Scratch platform. While such an approach is important for students who are new to a topic (Jacob et al., 2020), curriculum designers should also consider incorporating activities for full creative freedom among underrepresented students to develop a sense of what the act of "coding" entails.

While utility, perception, and interest were not quantitatively significant in our models, we want to stress how that finding does not imply these factors are not present. Rather, our interviews indicate otherwise. Our mixed-method approach allows us to see how the students interact with coding from the perspective of these other factors, even if they may not be as present or as significant as confidence and social values. Future work can continue to explore the interplay between these factors.

Demographic factors

There were no consistent patterns across ELL designation and Gender as key moderators for ESCAS. The insignificant findings align with mixed findings on attitude differences between social groups (Carlone et al., 2014; Maltese, Melki, & Wiebke, 2014). In the case of multilingual students, the lack of curricula that is culturally relevant and inclusive of their linguistic background negatively impacts their motivation toward the field (Beier et al., 2019). Studies have found that culturally responsive teaching and hands-on inquiry approaches supported multilingual students' engagement and motivation in CS (; Dou et al., 2019). Seeing that designation as an English Language Learner is not a significant predictor of motivation changes, it can be due to elements of the curriculum and learning at home, where their culture and background is embraced. While we cannot identify the specific factors that can inform how ELL students were supported, our findings hint at the benefits of the integration of English Language Arts in computer science curricula and learning code at home.

Gender was incorporated to consider whether their gender identities influence their attribution towards coding (Pratkanis & Greenwald, 1989). Our findings show that there are no gender differences in attitude changes upon exposure to a year long remote curriculum. This differs from the growth of studies that found gender differences in attitudes towards computer science among elementary level students. A study found that among 4th-6th graders, boys displayed greater confidence and interest in CS/STEM than girls (Dou et al., 2019). Similarly, male students have been found to exhibit higher CS attitudes than their female counterparts in elementary (Vandenberg et al., 2021).

Given the remote nature of our study, we must acknowledge that our findings do not provide sufficient evidence to conclude that Latinx students' early coding attitudes are unaffected by their gender identities. Unlike most computer science interventions in the literature, our study involved a remote curriculum where students learned to code for the first time at home, rather than in a traditional classroom environment. According to Eccles et al. (1983), gender differences in attitudes and goals are influenced by social and cultural forces that constantly shape individuals' self-schema. In our case of remote learning, students were navigating a new topic. While parents are key socializers in the household, the new topic of coding is unfamiliar and new just like the student. Moreover, the remote learning environment posed challenges in terms of natural collaboration and interaction among peers, which are factors that can significantly impact students' self schema as a coder and diverse identities, including gender.

Furthermore, it is important to address the limitations of the measurement tool used in this study and the necessity of explicitly incorporating items that capture the social forces contributing to gender disparities. The ESCAS measure included items related to stereotypes but may not have been adequately tailored to our sample population, which predominantly consisted of white individuals with a reasonable gender representation (Mason & Rich, 2020). To better capture the nuances of gender influences, future research should focus on developing stronger measurement items that consider the diverse social and cultural factors affecting Latinx students' attitudes towards coding.

Conclusion

This study focused on changes in coding attitudes among Latinx students following exposure to a remote coding curriculum, supported by both quantitative and qualitative evidence to gain deeper insights into how attitudes were portrayed. Recognizing that attitudes provide a glimpse into developing identities that can influence educational opportunities, our findings made a meaningful contribution to the growing field of elementary computing and motivation. The study revealed how early exposure to a remote coding curriculum resulted in significant changes to coding confidence and the perception of social values among parents and peers. Qualitative findings unveiled that students relied on values that informed their confidence and approach to coding projects, specifically perseverance and the importance of helping family. Examination of mean differences highlighted the need to explicitly address confidence in specific coding skills. Additionally, we uncovered the role that creativity played in developing interest and discussed the limitations of a yearlong exposure to a curriculum and the use of a single platform on utility and perception of coders. Various opportunities for future research were suggested, particularly focusing on factors that influenced early coding motivation among Latinx students, such as cost, stereotypes, and cultural values.

Limitations

Our study and findings are subject to several limitations that should be acknowledged. Firstly, the absence of a control group in our research design prevents us from establishing a relationship between ESCAS outcomes and the curriculum intervention or the remote learning environment. Secondly, our analysis of attitudes was constrained by the coding constructs identified by the validated measure for elementary-aged students. We have acknowledged and described the limitations of this measure and have proposed avenues for improvement, which have implications for the development of more comprehensive measures of early coding motivation.

Furthermore, future research should explore the comprehensive SEVT framework that encompasses coding attitudes. In particular, it is crucial to consider the costs, attainment values, and extended socializers associated with the participation of underrepresented students in coding learning experiences, taking into account their diverse identities. Nonetheless, our findings shed light on the initial coding attitudes of a group that has been understudied, primarily due to their young age and ethnic background.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author, Leiny Garcia. The data are not publicly available due to containing information that could compromise the privacy of research participants.

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Appendix A

Correlation Tables

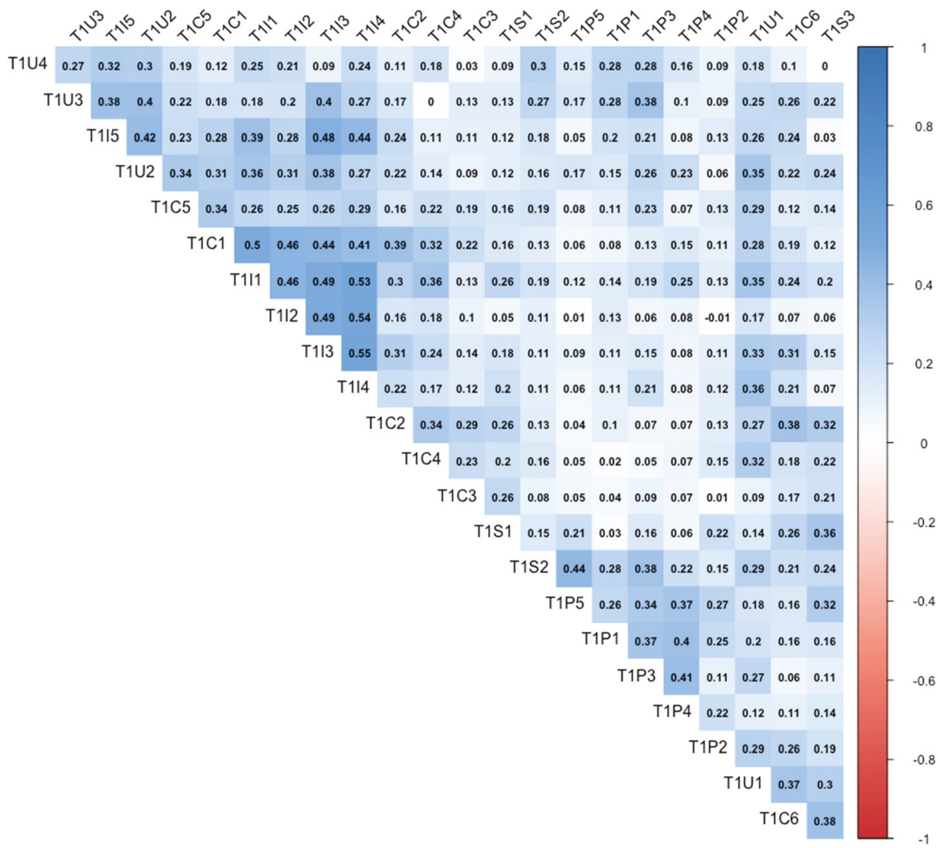

Figure A1.
Correlation matrix of pre-test (time 1) unweighted scores. *Note*: Positive correlations are in blue, negative correlations are in red, and color intensity alludes to correlation coefficients.

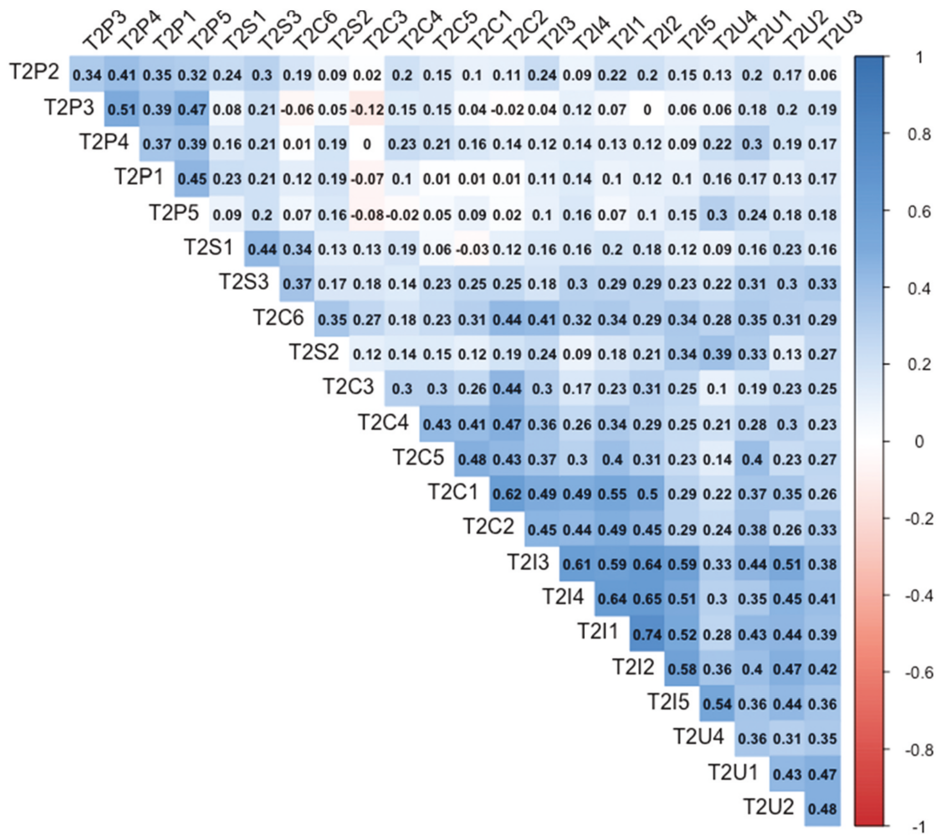

Figure A2.
Correlation matrix of post-test (time 2) unweighted scores. *Note*: Positive correlations are in blue, negative correlations are in red, and color intensity alludes to correlation coefficients.

Appendix B

Plots to Check for Normality Assumption

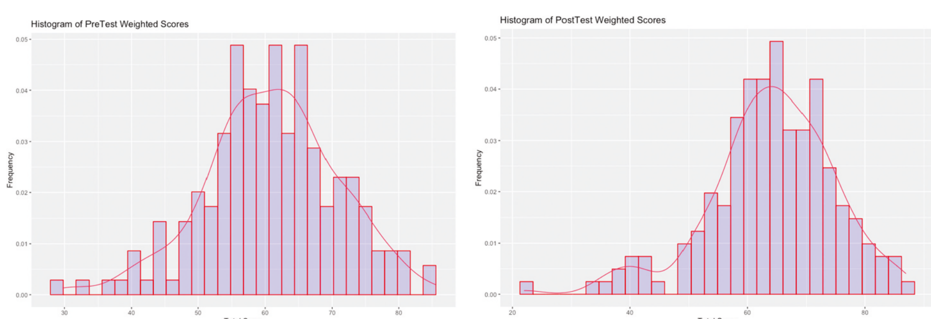

Figure B1.
Distribution of weighted test scores.

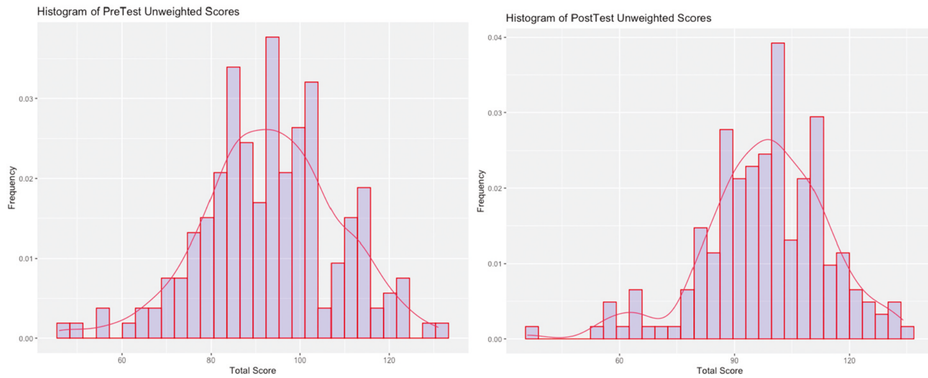

Figure B2.
Distribution of unweighted test scores.

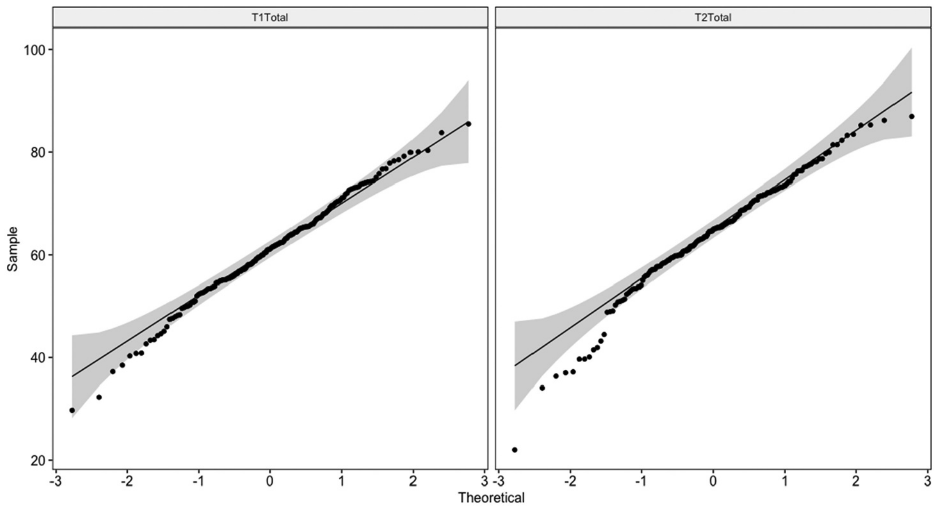

Figure B3.
QQ plot of total weighted score.

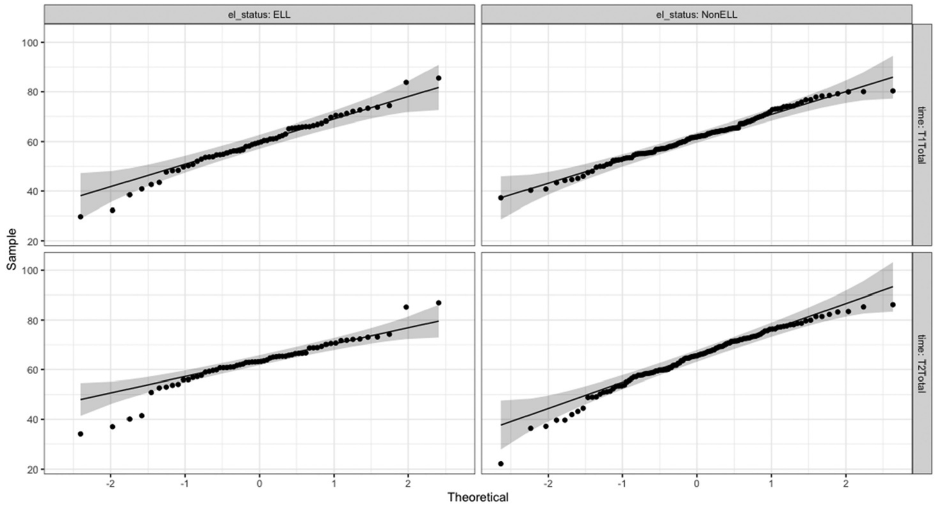

Figure B4.
QQ plot of weighted total score by time and ELL designation.

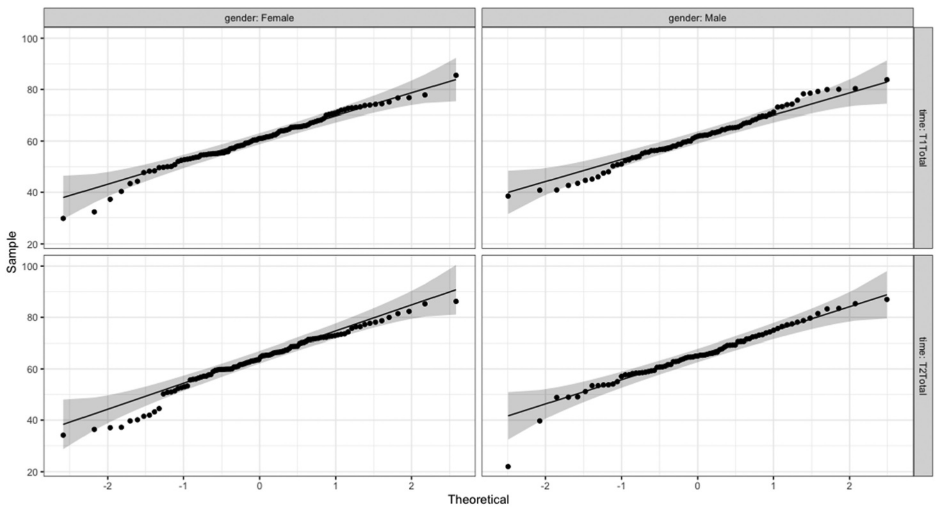

Figure B5.
QQ plot of weighted total score by time and gender.

Appendix C

Total Weighted Score Box Plots

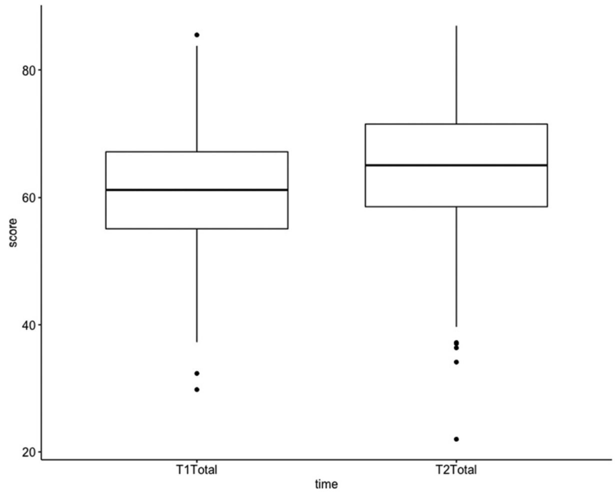

Figure C1.
Total weighted score between time 1 (pretest) and time 2 (posttest).

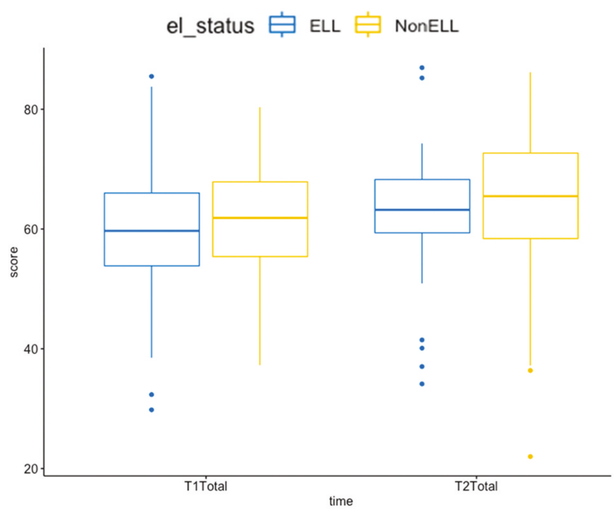

Figure C2.
Weighted total score between time grouped by designation of ELL.

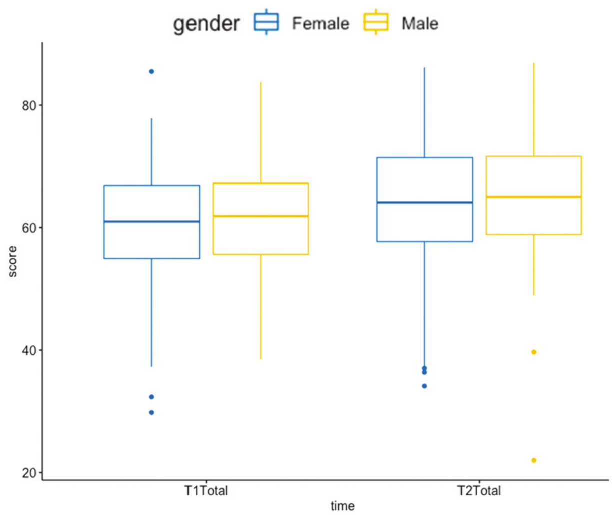

Figure C3.
Weighted total score between time, grouped by gender.

Appendix D

Interest (I) Weighted Score Box Plots

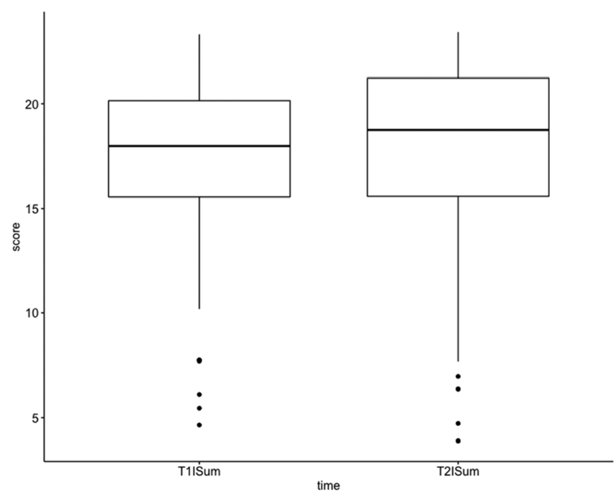

Figure D1.
Interest weighted score between time 1 (pretest) and time 2 (posttest).

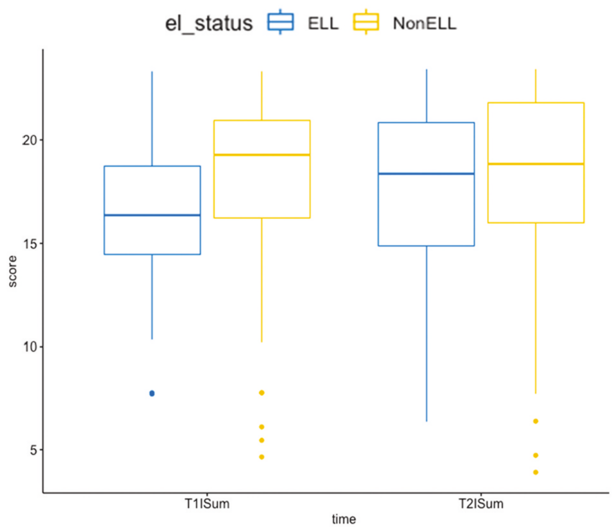

Figure D2.
Interest weighted score between time,Grouped by designation of ELL.

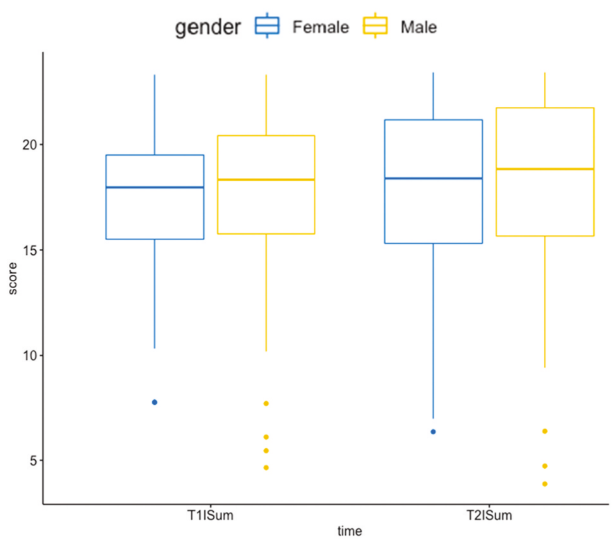

Figure D3.
Interest weighted score between time, grouped by gender.

Appendix E

Confidence (C) Weighted Score Box Plots

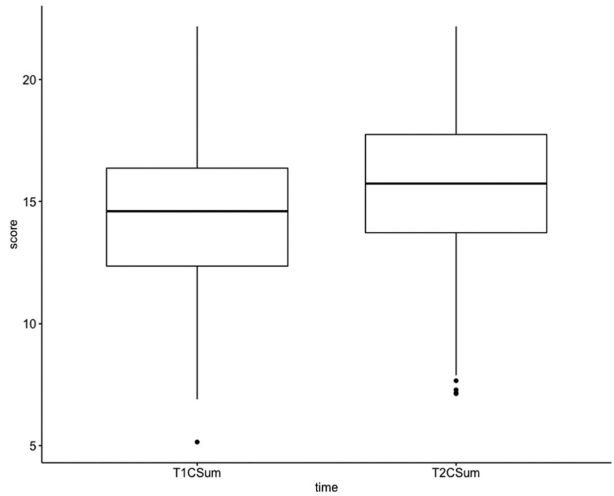

Figure E1.
Confidence weighted score between time 1 (pretest) and time 2 (posttest).

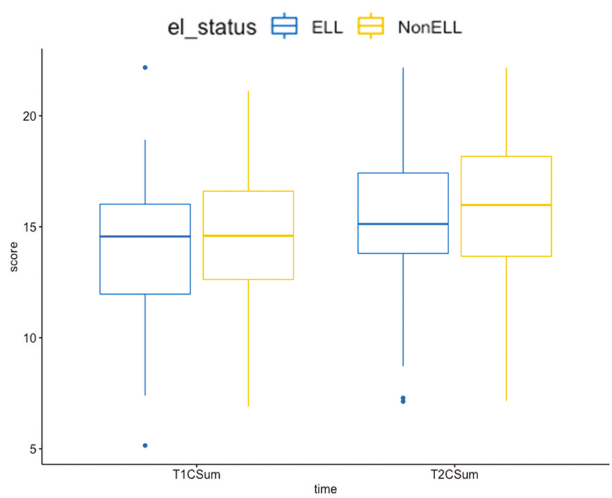

Figure E2.
Confidence weighted score between time, grouped by designation of ELL.

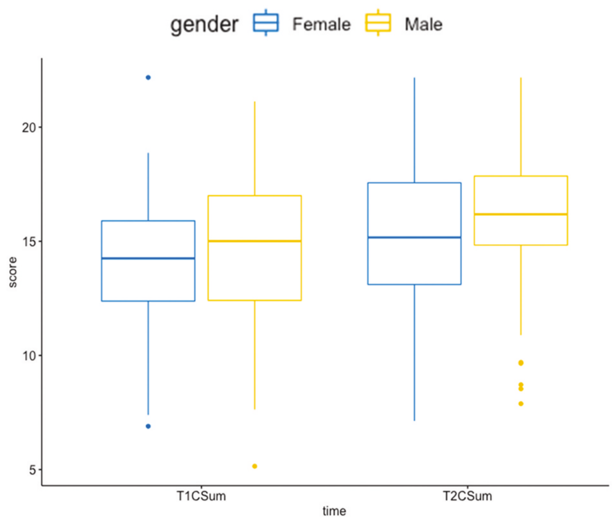

Figure E3.
Confidence weighted score between time, grouped by gender.

Appendix F

Utility (U) Weighted Score Box Plots

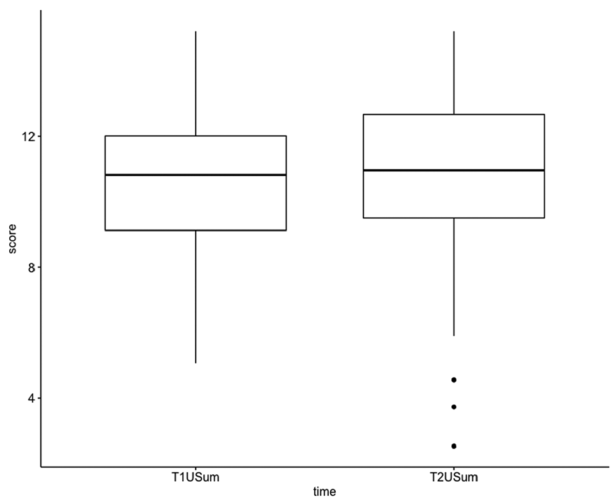

Figure G1.
Utility weighted score between time 1 (pretest) and time 2 (posttest).

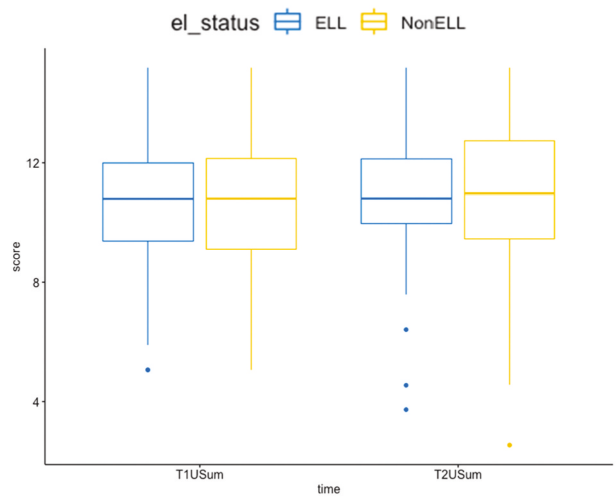

Figure F2.
Utility weighted score between time,Grouped by designation of ELL.

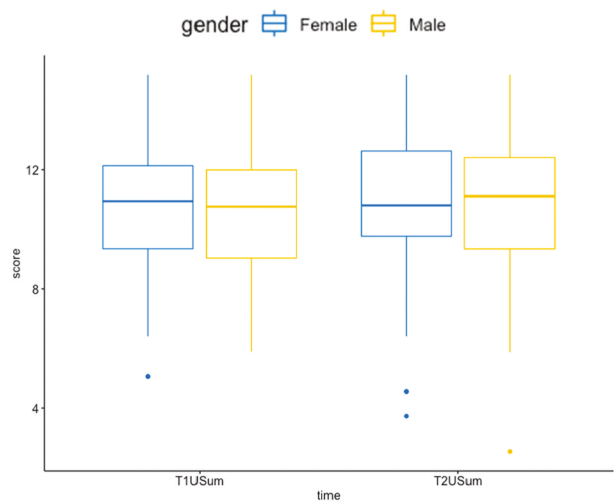

Figure F3.
Utility weighted score between time, grouped by gender.

Appendix G

Social Values (S) Weighted Score Box Plots

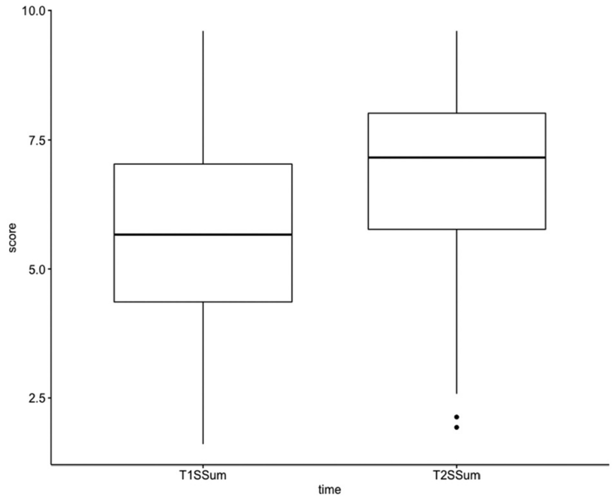

Figure G1.
Social values weighted score between time 1 (pretest) and time 2 (posttest).

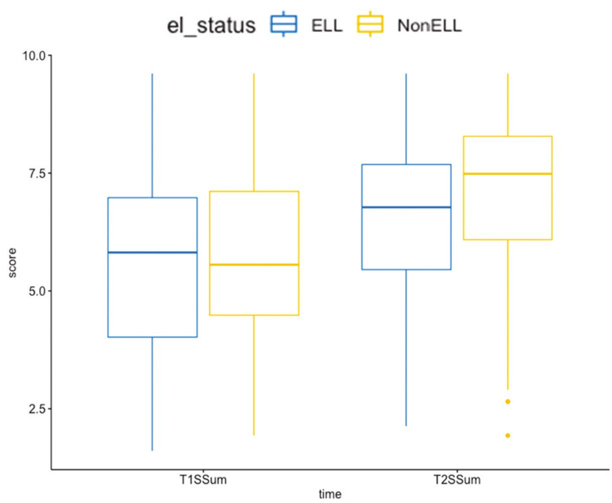

Figure G2.
Social values weighted score between time, grouped by designation of ELL.

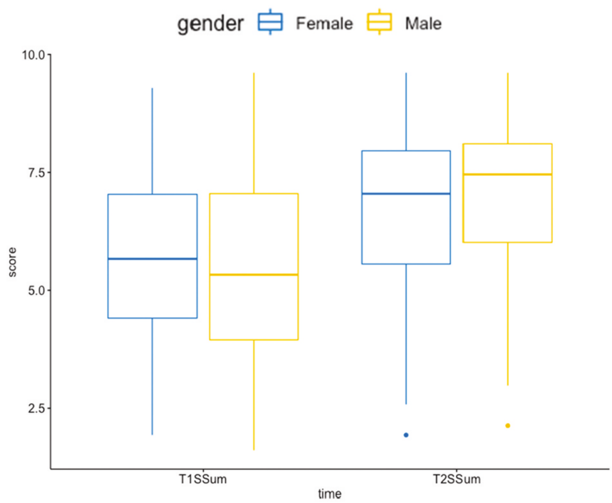

Figure G3.
Social values weighted score between time, grouped by gender.

Appendix H

Perception of Coders (P) Weighted Score Box Plots

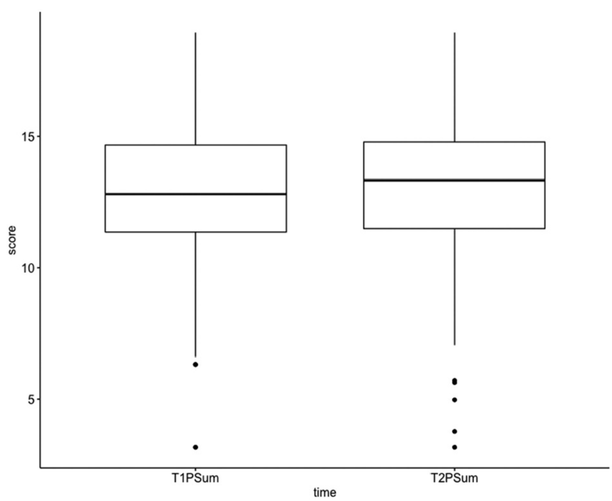

Figure H1.
Perception of coders weighted score between time 1 (pretest) and time 2 (posttest).

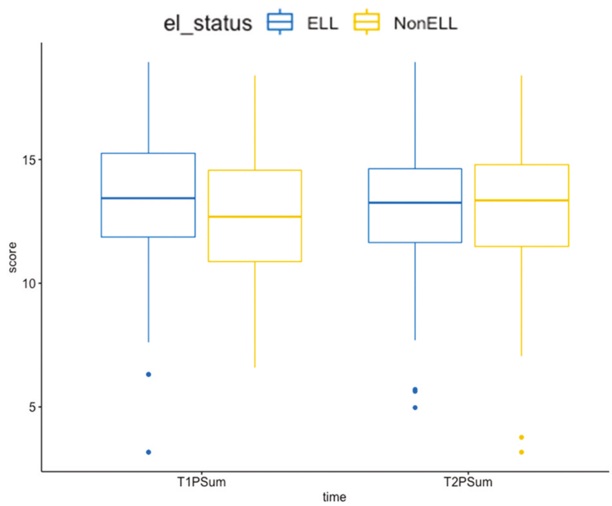

Figure H2.
Perception of coders weighted score between time, grouped by designation of ELL.

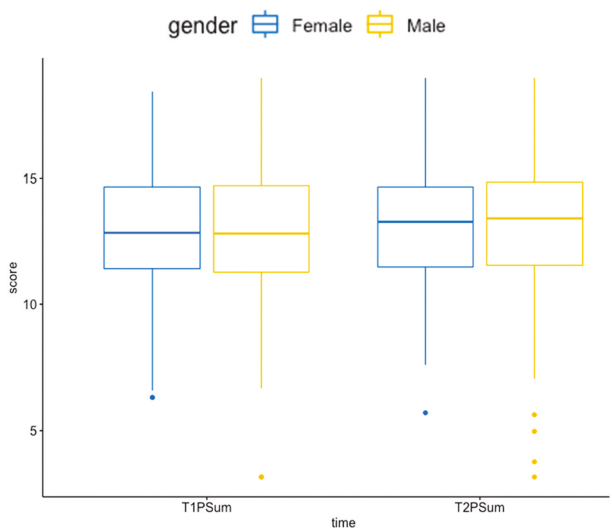

Figure H3.
Perception of coders weighted score between time, grouped by gender.

Appendix I

Modified Interview Protocol
Warm Up Questions

- What are some of your favorite things to do for fun outside of class?
- Do you like school? What do you like about school?

General CS Views

- When I say "computer scientist" what person comes to your mind?
- Do you think computer scientists can make this world better? If so, how do you think they can improve the world?

Scratch Projects

- Do you like coding your scratch projects? Tell me more about that.
- Do you think that you can learn coding well? Why or why not?
- How do you feel when you make a mistake in your program?
- Give one example of a time when you made a mistake. Did you fix it? If so, how did you fix it?

Social Values

- Have you ever shared your coding projects outside of school with family and friends? If so, how did they react or what did they say?