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Exploring Gender Differences in Computer Science Motivation Among Japanese Primary School Students

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Abstract

This study aimed to examine gender differences in the computer science motivation of Japanese primary school students using Eccles' expectancy-value theory and to explore the motivational factors contributing to such differences. The results suggested that girls had lower self-efficacy, less interest in learning programming, and a greater concern about failure in programming than boys. Furthermore, within the components of the expectancy-value theory, sixth-grade girls may have initiated their motivation for learning programming with intrinsic value before extending it to other components. These findings indicate that gender differences in computer science motivation may emerge as early as primary school and point to potential motivational factors that may underlie these differences.
Keywords: gender differences, programming, primary school students, expectancy-value theory

1 Introduction

1.1 Background

With the advancement of technology, society has changed drastically, leading to an increased demand for human capital in science, technology, engineering, and mathematics (STEM) fields. For example, Fayer et al. [1] addressed that the net growth of employment in STEM occupations was more than five percentage points higher than that of non-STEM occupations between May 2009 and May 2015. However, the share of female graduates in STEM fields was less than that of male graduates in many countries, with the OECD average at 32 %, and Japan has the lowest ranking among OECD countries at 17 % [2]. Not only was the share of female graduates low, but Japan also had the lowest share of female university students enrolling in STEM fields among OECD countries. Female students in Japan comprised only 16 % of the engineering, manufacturing and construction fields, the lowest among OECD countries [3]. Concerning the gender gap in STEM fields, the working group of the Council for Science, Technology and Innovation [4]

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presented a policy package for the development of human capital in a society where technology is rapidly advancing, including narrowing the gender gap in STEM fields.

Even though the gender gap in the STEM fields has been recognized as crucial for policy in Japan, there are not enough studies on it. According to Oda et al. [5], of the literature review they conducted regarding the gender gap in STEM fields from primary and secondary education to higher education in Japan, mathematics and science accounted for 82% of the studies in which subject names were identified, whereas computer science was among the few. Additionally, Oda et al. [6] conducted a literature review on the gender gap in computer science from primary and secondary education to higher education outside of Japan. They found that the majority of studies they examined were focused on higher education, with only a few targeting primary schools. Given that learning in primary schools serves as the foundation for later education, it can be said that further research is necessary to investigate the reasons behind the gender gap in computer science and apply them to practices.

The remainder of the paper is composed as follows. Section 2 introduces related work. Section 3 explains the methodology, including the methods of the survey and semi-structured interviews. Section 4 presents the results of the *t*-test analysis of the survey and the content analysis of the semi-structured interviews, followed by a discussion of the findings in Section 5. Section 6 concludes the study by highlighting its implications and suggesting directions for future research.

2 Related Work

One of the theoretical foundations for explaining achievement goals and behaviors of educational and career choices is Eccles's expectancy-value theory. Expanding on Atkinson's theory of achievement motivation [7], Eccles et al. [8] postulated that the theoretical model encompasses two sets of beliefs: the individual's expectations for success and subjective task values, grounded in substantial empirical evidence from real-world tests [9]. Eccles and her colleagues believed that these two components "are the most immediate or direct predictors of achievement performance and choice" [9, p.56]. Eccles and Wigfield [10] defined expectations for success as an individual's beliefs regarding their performance for a given task or activity in the future. Subjective task values, as illustrated by Eccles and Wigfield [10], encompass various achievement tasks and how these characters influence an individual's motivation to engage in some tasks over others. According to Eccles and Wigfield [10], four components significantly impact subjective task values: attainment value, intrinsic value, utility value, and perceived cost [9]. Attainment value pertains to the subjective importance of performing well on a given task, directly linked to an individual's social role identities [10]. Intrinsic value denotes the enjoyment derived from engaging in the task [9] [10]. Utility value encompasses how a task aligns with an individual's future plans [9]. Perceived cost represents what the individual must sacrifice to undertake a task [9]. The first three components explain the positive perspective of subjective task values; however, perceived cost entails the negative perspective of subjective task values and encompasses three sub-concepts. According to Eccles [11], three sub-concepts comprising perceived cost are: (1) the amount of effort needed to succeed (effort cost), (2) the loss of time that could be used to engage in other valued activities (opportunity cost), and (3) the psychological meaning (psychological cost).

Therefore, the purpose of this study is to explore gender differences in student motivation for computer science, employing Eccles' expectancy-value theory, which contributes to the prediction of academic and occupational choices. Specifically, this study investigates gender differences in motivation among Japanese primary school students and examines the observed gender differences in motivation for computer science and the factors contributing to these differences. The study is guided by two research questions:

RQ1 What gender differences are observed in motivation for computer science among primary school students.
RQ2 What factors contribute to the gender differences in motivation for computer science among primary school students.

3 Methodology

The methodology employed in this study consists of two sequential steps: performing a survey to evaluate the motivation of primary school students in computer science, utilizing Eccles' expectancy-value theory, and conducting semi-structured interviews with students who participated in the survey. The main objective of the first step is to address research question 1, while the second step is designed to address research question 2. The following sections will elaborate on the methodology of the two steps.

3.1 Survey

3.1.1 Participants

The participants comprised 29 sixth-grade students in Japan, comprising 15 girls and 14 boys. Each student was provided with an individual laptop computer in class and was authorized to take the laptop home. The students were given the autonomy to decide whether to utilize the laptops outside of class. Throughout the sixth grade, every student utilized a laptop computer in each subject during every class. Regarding computer science education, sixth-grade students were exposed to programming concepts through unplugged activities for one hour during their school year in science class. While there was little instruction in programming within the classes, students were free to utilize Scratch, a visual programming language installed on their laptop computers, during recess and after class.

3.1.2 Instruments

The survey included demographic questionnaires and questionnaires based on the expectancy-value theory.

The demographic questionnaires comprised questions regarding gender, the frequency of programming experience both inside and outside of school, and the frequency of computer use at home to assess students' computer use tendencies. The questionnaire assessing the frequency of in-school programming experience employed a 5-point Likert scale (5, at least once a week; 4, about two or three times a month; 3, about once every few months; 2, less than the above; 1, I don't know or never). In addition, the questionnaire on the frequency of out-of-school programming experience asked whether students have had out-of-school programming experience and, if so, specific examples. The questionnaire asking the frequency of computer use at home adopted a 4-point Likert scale (4, almost every day; 3, sometimes; 2, rarely; 1, never). The inclusion of the last question resulted from considering that students used a laptop computer in every class during their 6th grade year. Under these circumstances, the estimated frequency of computer use at home could be an indicator for estimating students' tendency to use computers, since the frequency of computer use at school would not change.

The questionnaires based on the expectancy-value theory included items pertaining to both expectations for success and subjective task values, which comprised positive and negative subjective task values, as addressed in section 2.

The survey items for expectations for success employed the self-efficacy scale proposed by Harada et al. [12], comprising a 6-item self-efficacy measurement on a 6-point Likert scale (6, very applicable, to 1, not applicable at all). To develop this scale, Harada et al. [12] referred to the items proposed by Suzuki et al. [13] to examine middle school students' motivation for observing and experimenting in science based on Eccles's [11] expectancy-value theory. Since the scale proposed by Harada et al. [12] was originally designed to assess the same subjects as those in Suzuki et al.'s [13] study, the term "science observation and experiment" was replaced with "learning programming" in this study. Higher scores on this scale indicate higher self-efficacy in programming. Given the utilization of self-efficacy scales in assessing expectations for success in prior studies (e.g., [14]), this research also adopted them as the scale for measuring expectations for success.

In terms of survey items assessing positive subjective task values, this study utilized the scale formulated by Kera and Nakaya [15], comprising 13 items measured on a 5-point Likert scale (5, very applicable, to 1, not applicable at all). Kera and Nakaya [15] conducted a factor analysis of a survey administered to middle school students in science, employing items related to Eccles's [11] three components of positive subjective task value: attainment value, intrinsic value, and utility value. Following the factor analysis, a positive task value scale was developed, encompassing attainment value (3 items), intrinsic value (4 items), practical utility value (3 items), and institutional utility value (3 items). The term "science contents" in the questionnaire was replaced with "learning about programming." Higher scores on this scale indicate higher levels of attainment value, intrinsic value, and utility value associated with learning programming.

Regarding the survey items concerning negative subjective task values, this study employed the scale developed by Kera and Nakaya [16], containing 11 items measured on a 7-point Likert scale (7, very applicable, to 1, not applicable at all). Kera and Nakaya [16] measured perceived cost among college students who took psychology classes, utilizing a scale including three variables influencing perceived cost as proposed by J. Eccles [11]. The three variables integrated into this scale, including opportunity cost (4 items), effort cost (4 items), and psychological cost (3 items) [16]. Within the questionnaire, "psychology learning content" was substituted with "learning about programming." Higher scores on this scale signify increased perceived cost associated with learning programming, suggesting that higher scores impede motivation to engage in specific activities such as learning programming.

3.1.3 Data Collection and Analysis

In February 2023, marking the end of the school year in Japan, we conducted a survey on children. This survey utilized demographic questionnaires and questionnaires grounded in the expectancy-value theory. Subsequently, we conducted a comparative analysis of the results obtained from girls and boys, examining differences in the means of each item through an independent samples *t*-test.

3.2 Semi-Structured Interview

3.2.1 Participants

The participants were two girls selected from the survey respondents. Specifically, as outlined in

Section 4, there were marginal gender differences in the mean total scale scores, particularly in the self-efficacy, intrinsic value, and psychological cost scales. While not all differences reached statistical significance, effect sizes indicated substantial differences in these areas. These two participants were chosen for semi-structured interviews based on their different trends in the survey responses: Student A exhibited higher scores on these scales, whereas Student B exhibited lower scores. The aim was to explore what factors may have contributed to these differing motivational profiles. No other students participated in the semi-structured interviews. Note that both students achieved similar grades and were among the highest in their class.

3.2.2 Data Collection and Analysis

The semi-structured interviews were conducted by one of the authors approximately two weeks after the survey, with each interview lasting around six minutes. Before starting the interview, the author outlined the purpose of the interview, assured participants about the confidentiality of their individual information, and explained that the interview would not affect their grades. The main questions asked were if participants had discussed programming outside of school with family or friends, the content of those discussions, and their level of interest in programming and its underlying reasons. The sequence of the questions was flexibly adjusted based on participants' responses.

The interview sessions were recorded using a smartphone and were subsequently transcribed. The transcribed text was then segmented into sentences while preserving their intended meanings. To identify the factors that may contribute to the different trends observed between Students A and B, the sentences were tagged and categorized. Specifically, the components of the expectancy theory, as delineated in Section 3.1.2, were reviewed against their respective definitions and tagged to the corresponding sentences. Throughout this process, certain sentences received multiple tags if considered applicable to multiple definitions, while others remained untagged.

Subsequently, the sentences were categorized into three factors that could influence gender differences: individual, relational, and structural factors. These factors are informed by literature studying gender differences in STEM fields [17] [18] [19]. The individual factor encompasses aspects of individual motivation, including self-efficacy, interest, and past experiences [19]. The relational factor pertains to the roles of family and peers, encompassing aspects such as their intentions and encouragement regarding the child's career path [17]. The structural factor is associated with the educational system or entrance examination system [19]. These three factors were examined according to their respective definitions, and each sentence was classified into one of those factors if it conformed to one of those definitions. There was no duplicate classification of each sentence with respect to these three factors; all sentences were classified.

4 Results

4.1 Research Question 1: What gender differences are observed in motivation for computer science among primary school students

4.1.1 *Participants' demographics*

Table 1 presents a summary of the mean scores from the participants' demographic questionnaire, which includes the frequency of programming experience at school and the frequency of computer use at home. Girls scored slightly higher than boys in terms of the frequency of computer use, while boys scored higher than girls in the frequency of programming experience at school. Although the mean scores showed different trends for girls and boys, the *t*-test results indicated no significant differences between the two groups. Concerning programming experience outside of school, a total of six participants—three girls and three boys—indicated that they had experience with programming outside of school.

Table 1: Frequency of Computer use and Programming Experience

Variable	Girls		Boys		*t*-value
	M	*SD*	*M*	*SD*	
Computer use	3.13	0.52	2.93	0.83	0.80
Programming experience at school	2.40	1.40	3.29	1.59	1.59

n = 29 (15 girls, 14 boys)

4.1.2 *Participants' motivation for programming*

Tables 2 to 4 present summaries of the mean scores for expectations for success, positive subjective task values, and negative subjective task values, respectively. Cronbach's α ranged from 0.75 to 0.95, indicating strong internal consistency for each variable and confirming the reliability of the measurements. Boys (M = 4.26, SD = 0.96) scored higher than girls (M = 3.61, SD = 0.76) on expectations for success, with a marginally significant difference, $t(27) = 2.04$, $p = .051$. The effect size was large (d = 0.76), indicating a substantial practical difference. A trend toward significance was also observed for intrinsic value, with boys (M = 4.27, SD = 0.95) reporting higher values than girls (M = 3.55, SD = 1.09), $t(27) = 1.88$, $p = .071$. The effect size was large (d = 0.70), suggesting meaningful differences. In addition, girls (M = 2.96, SD = 1.48) reported higher psychological costs than boys (M = 2.21, SD = 1.22), though the difference was not statistically significant, t (27) = 1.46, p = .155. The effect size was medium (d = –0.54), indicating that girls experienced moderately higher psychological costs than boys, which may suggest a practically relevant difference despite the lack of statistical significance. No significant differences were observed in the mean scores of the other scales. The mean scores of each item by gender are shown in Appendices 1−3.

Table 2: Expectations for Success

Variable	Girls		Boys		α	*t*-value	*d*
	M	*SD*	*M*	*SD*			
Expectations for Success	3.61	0.76	4.26	0.96	0.94	2.04 †	0.76

Note. † p < .10; n = 29 (15 girls, 14 boys), α represents Cronbach's α, and d represents Cohen's d.

Table 3: Positive Subjective Task Values

Variable	Girls		Boys		α	*t*-value	*d*
	M	*SD*	*M*	*SD*			
Attainment Value	3.60	0.69	3.79	0.79	0.77	0.67	0.25
Intrinsic Value	3.55	1.09	4.27	0.95	0.95	1.88 †	0.70
Practical Utility Value	3.71	0.88	4.05	0.79	0.83	1.08	0.40
Institutional Utility Value	4.16	0.68	4.26	0.83	0.87	0.38	0.14

Note. † p < .10; n = 29 (15 girls, 14 boys), α represents Cronbach's α, and d represents Cohen's d.

Table 4: Negative Subjective Task Values

Variable	Girls		Boys		α	t-value	d
	M	SD	M	SD			
Opportunity Cost	3.12	1.25	3.27	1.19	0.75	0.33	0.12
Effort Cost	4.40	1.27	4.20	1.46	0.87	0.40	-0.15
Psychological Cost	2.96	1.48	2.21	1.22	0.85	1.46	-0.54

Note. n = 29 (15 girls, 14 boys), α represents Cronbach's α, and d represents Cohen's d.

4.2 Research Question 2: What factors contribute to the gender differences in motivation for computer science among primary school students

Table 5 presents an overview of the interview analysis, showing the number of sentences extracted from the interview transcriptions of Students A and B, the sentences tagged as components of the expectancy-value model, and the categories of factors influencing gender differences.

In the case of Student A, 25 sentences were extracted from the interview transcription. Regarding tagging based on the components of the expectancy-value model, four sentences were tagged with expectations for success, four with practical utility value, and 13 with intrinsic value, indicating that most of the sentences were related to intrinsic value. Concerning the three factors influencing gender differences, seven out of 25 sentences were classified as the individual factor, while 18 were classified as the relational factor. The majority of the sentences were classified as the relational factor.

Contrastingly, Student B generated 11 sentences from the interview transcription. Concerning tagging based on the components of the expectancy-value model, two sentences were tagged with practical utility value, and six were tagged with intrinsic value, suggesting most of the sentences were related to intrinsic value. Although this trend is similar to Student A, the number of sentences classified as intrinsic value was half that of Student A, and the content related to intrinsic value was mostly negative, encompassing factors such as lack of interest and reluctance to engage in programming. Regarding the three factors influencing gender differences, nine sentences were classified as the individual factor, with only two classified as the relational factor. This result differs from that of Student A, where relational factors tended to dominate.

Table 5: Outline of Interview Analysis

	Student A	Student B
Total sentences	25	11
Expectancy-value theory components	Expectations for success (4) Practical utility value (4) Intrinsic value (13)	Practical utility value (2) Intrinsic value (6)
Gender differences influencing factors	Individual factor (7) Relational factor (18)	Individual factor (9) Relational factor (2)

Note. Student A is a girl with high motivation to learn programming, while Student B is a girl with low motivation to learn programming.

5 Discussion

5.1 Gender Differences in Motivation for Computer Science

Regarding the first research question, this study found marginally significant differences in both expectations for success and intrinsic value, with boys scoring higher than girls on both measures. In contrast, psychological costs tended to be higher among girls than boys, although this difference was not statistically significant ($p = .155$); however, the effect size was moderate ($d = -0.54$), suggesting a potentially meaningful disparity. These findings suggest that girls may exhibit lower self-efficacy, less interest in learning programming, and a heightened concern about failure in programming compared to boys. Although no significant difference was observed between girls and boys in terms of the frequency of programming experience at school, this trend may be related to the fact that boys' mean score on programming experience was higher than those of girls, which may, in turn, contribute to their greater expectations for success and intrinsic motivation.

Expectations for success, which measure self-efficacy, and psychological costs are similar in assessing an individual's belief in their competency to execute a desired action. Therefore, this section discusses both self-efficacy and psychological costs collectively. The results of this study align with research on gender differences among college students taking computer science courses, encompassing measurements of both self-efficacy and students' performance [20] [21]. These studies reveal significant differences in self-efficacy scores between girls and boys, with girls scoring lower than boys, while students' performance remains unaffected. Numerous studies support the relationship between self-efficacy and career choice. Drawing from Bandura's self-efficacy theory [22], Taylor and Betz [23] illustrated that students lacking self-efficacy tended to be indecisive about their career choices. Additionally, they observed little or no correlation between ability level and self-efficacy expectations regarding career decision-making tasks, implying that individual self-efficacy informs the outcomes of career choice. In a related study, Brauner et al. [24] presented the four principal source of information outlined in Bandura's self-efficacy theory [22]; personal experience, observation of models/peers, social support, and physiological reactions. In light of prior studies and the findings of this research, it is essential to make further efforts to enhance girls' self-efficacy by applying the principles of self-efficacy theory, fostering their aspirations for careers in computer science.

The study also revealed that the mean scores for intrinsic value were significantly higher in boys than in girls. These findings align with the research conducted by Brauner et al. [24], which investigated gender differences in the interest in computer science among sixth-grade students. Relatedly, Cheryan et al. [25] suggested that stereotypes associated with computer science and engineering contribute to diminished interest in these fields among girls. They argued that cultural stereotypes impact girls' choices and interests from an early stage, even before entering college. Addressing these stereotypes, studies have suggested that altering media portrayals, the presence of individuals in the field, and environmental factors could influence girls' interest in computer science [25] [26]. In this study, we demonstrated gender differences in intrinsic value in computer science as early as sixth grade. Further research on the relationship between intrinsic value and stereotypes among girls at this early stage is warranted.

5.2 Factors Influencing Gender Differences in Motivation for Computer Science

Concerning the second research question, the distinction between Student A and Student B lies in the number of sentences tagged with intrinsic value and their content. The number for Student

A exceeded that of Student B, and the content reflects a positive attitude toward learning programming, whereas all of Student B's content indicated negative interests. Additionally, the gender differences influencing factors also demonstrated a different trend between Student A and B. Student A had more than double the number of sentences categorized under the relational factor compared to the individual factor, while Student B's number of sentences categorized under the individual factor was more than four times that of the relational factor. In the following text, we will share the sentences extracted from the interview transcriptions, and the expectancy-value model components were added to each segmented sentence by square brackets.

Student A was introduced to programming through her interactions with boys in the same class, sparking an intrinsic interest in programming. She recounted, "It was a while ago when some boys were making noise together, so I peeked in and found a site called Scratch…When I checked it out, I thought, programming is surprisingly interesting [Intrinsic value]." Subsequently, she found attainment value in the increased interaction with boys in the same class through learning programming. In connection with this, she articulated, "Programming is quite an opportunity to talk to boys [Attainment value]," "I am glad that they (boys in the same class) are relying on me [Attainment value]." Additionally, receiving social support and observing role models both in person and online contributed to her self-efficacy. In relation to this, she mentioned, "By sharing my Scratch (programming work on the website), people can look at it and tell me what's good and where I can improve [Expectations for success]." She also encountered a statement that might lead to gender stereotyping in programming, stating, "When I showed a girl a lottery program I made, and she said she does not understand it at all, so I guess boys are more interested in programming [No tagging]." However, this event did not seem to significantly impact her interest in programming.

In contrast, Student B was introduced to programming through an invitation from her friend; however, she did not persist in programming. While acknowledging the importance of using computers in this information society, this attainment value did not align with her intrinsic motivation for programming. In connection with this, she expressed, "I think using a computer is important [Practical utility value], but it's tedious [Intrinsic value]." Given her negative intrinsic value for learning programming, her interactions with peers in this domain did not expand. In relation to this, she remarked, "I'm a bit unsure why it's so much fun (for the other students who engage in programming) [Intrinsic value]."

This interview was conducted with two girls whose trends in learning programming differed, aiming to explore the factors that affect gender differences in computer science observed in this study. As a result, this study found that Student A's and B's motivations for learning programming began with intrinsic value and then expanded to other components of motivation. Further investigation of the factors influencing students' motivation to learn programming is necessary in the future, while increasing the number of interviews and including more boys.

6 Conclusion

This study investigated gender differences in Japanese primary school students' motivation for computer science, utilizing Eccles' expectancy-value model. In addressing the first research question—examining gender differences in motivation for computer science among primary school students—this study suggested that girls may exhibit lower self-efficacy, are less interested in learning programming, and have an increased concern about failure in programming compared to boys. Regarding the second research question—exploring factors influencing gender differences in motivation for computer science among primary school students—the findings may suggest that, within the components of the expectancy-value model, sixth-grade girls initiated their motivation for learning programming from intrinsic value before extending it to other components. Further research is needed to increase the reliability of the factors influencing student motivation by increasing the number of participants and including more boys.

A limitation of this study is that it was conducted in a single primary school class, with analysis based on interviews with only two girls. This limitation introduces the potential for bias in the results and may limit the generalizability of the findings to a broader population of children. Further research should include (1) targeting upper grades, including lower and upper secondary school students, to investigate whether there are differences in motivation for computer science at each school level, (2) increasing the number of participants and interviews within the primary school setting to conduct similar studies, and (3) incorporating studies on the relationship between gender stereotypes and gender differences in motivation for computer science.

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Appendix

Appendix 1: Expectations for Success

	Item	Girls		Boys		t-value
		M	SD	M	SD	
Expectations for Success	I am able to focus when it comes to learning about programming.	3.80	0.94	4.57	1.02	2.12 *
	I am able to work very hard in learning about programming once I decide to do it.	3.53	1.13	4.36	1.01	2.07 *
	I am willing to learn about programming, even if I find it difficult.	3.67	0.90	4.21	1.05	1.51
	I am able to work on learning about programming without giving up even if I fail.	3.87	0.74	4.36	1.01	1.50
	I am able to tackle difficult problems without making mistakes in learning about programming.	3.33	0.90	4.00	1.11	1.78 †
	I am able to keep working until I succeed in learning about programming.	3.47	1.19	4.07	0.92	1.53

† $p < .10$, * $p < .05$; $n = 29$ (15 girls, 14 boys)

Appendix 2: Positive Subjective Task Values

	Item	Girls		Boys		t-value
		M	SD	M	SD	
Attainment Value	I think I can grow by understanding learning about programming.	3.93	0.80	4.00	0.96	0.20
	I think that learning about programming will bring me closer to my ideal self, the person I want to become.	3.40	0.74	3.43	0.85	0.10
	I think that people who know more about programming are smart people.	3.47	0.99	3.93	1.00	1.25
Intrinsic Value	I think the learning about programming is interesting.	3.67	1.18	4.29	1.14	1.44
	I think learning about programming is fun.	3.60	1.18	4.36	1.01	1.85 †
	I think learning about programming is boring#.	3.73	1.10	4.21	0.97	1.24
	I am interested in learning about programming.	3.20	1.21	4.21	0.97	2.48 *
Practical Utility Value	I think learning about programming is useful in my daily life.	4.00	1.00	4.07	1.07	0.19
	I think that learning about programming helps me to understand how things and phenomena around me work.	3.53	0.99	3.93	0.73	1.22
	I think that knowing about programming can help me in my daily life.	3.60	0.99	4.14	1.03	1.45
Institutional Utility Value	I think learning about programming is important for my future work.	4.13	0.74	4.21	0.97	0.25
	I think learning about programming will be useful when I grow up.	4.47	0.64	4.36	0.93	0.37
	I think learning about programming is important for middle school and high school.	3.87	0.83	4.21	0.89	1.08

† $p < .10$, * $p < .05$; $n = 29$ (15 girls, 14 boys); # reversed item; the values have been reversed.

Appendix 3: Negative Subjective Task Values

	Item	Girls		Boys		*t*-value
		M	*SD*	*M*	*SD*	
Opportunity Cost	I think that learning about programming will leave less time for my hobbies.	3.33	1.76	3.29	1.73	0.07
	I think that learning about programming leaves less time for other things I want to do.	3.40	1.55	3.43	1.95	0.04
	I think that in order to better understand learning about programming, I need to spend less time doing other things that I want to do.	3.07	1.44	3.00	1.36	0.13
	I think that in order to better understand learning about programming, I need to study programming while giving up activities that I like to do.	2.67	1.40	3.36	1.60	1.24
Effort Cost	I think I have to study very hard in order to better understand learning about programming.	4.53	1.51	4.43	1.65	0.18
	I think I have to put in a lot of effort in order to better understand learning about programming.	4.87	1.25	4.29	1.68	1.06
	I think I have to spend a lot of time in order to better understand programming.	4.40	1.64	4.64	1.65	0.40
	I think I have to spend more time studying than in other subjects in order to better understand learning about programming.	3.80	1.42	3.43	1.95	0.59
Psychological Cost	If I don't understand what I'm learning about programming, I feel miserable.	3.07	1.49	2.43	1.55	1.13
	I would feel embarrassed if I didn't understand learning about programming well.	2.93	1.79	2.07	1.38	1.44
	I would feel anxious if I can't understand learning about programming well.	2.87	1.68	2.14	1.41	1.25

n = 29 (15 girls, 14 boys)

Note. The data for Appendices 1–3 are from "Gender Differences in Programming among Primary School Students in Japan" by Oda et al. [27]. *T*-values and significance levels were calculated and added by the authors.